A METHOD TO RELATE PRODUCT TOLERANCING DECISIONS TO ENVIRONMENTAL IMPACTS AND COSTS IN MANUFACTURING

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A METHOD TO RELATE PRODUCT TOLERANCING DECISIONS TO ENVIRONMENTAL IMPACTS AND COSTS IN MANUFACTURING

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NOMENCLATURE

List of Abbreviations

ABC	Activity Based Costing
CAD	Computer Aided Design
CAE	Computer Aided Engineering
CAM	Computer Aided Manufacturing
CAPP	Computer Aided Process Planning
CBR	Case Based Reasoning
CER	cost estimating relationship
cf	cubic feet
cfm	cubic feet per minute
DfC	Design for Cost
DfE	Design for Environment
DfM	Design for Manufacturing
EI-99	Eco-Indicator 99; an indicator for quantifying environmental impacts
FBC	Feature-Based Costing

FLA	full load amperage [A]
gph	gallons per hour
HPR	hourly production rate [no. parts / hr]
HPY	hours per year [hrs / year]
kWh	kilowatt hour
LCA	Life Cycle Analysis / Assessment
mpt	millipoint; measure of environmental impact by EI-99 scheme
MRR	material removal rate [volume / time]
NVH	noise, vibration, and harshness
SPS	single point score [millipoints / part]; sum of environmental impacts
VBA	Visual Basic for Applications
WIP	work in progress

List of Symbols

C_{acq}	acquisition cost of one machine [$ / machine]
C_{labor}	financial cost of hourly labor [$ / hr]
C_{Q}	yearly consumables cost for one machine [$ / yr]

C_{tool}	yearly tooling cost for one machine [$ / yr]
C_{total}	total financial cost to produce one unit [$ / part]
f	machine fraction
f	feed rate [length / time]
I	electrical current [A]
$N_{machines}$	number of machines
$N_{operators}$	number of operators on a production line
$P_{electrical}$	electrical power [kW]
R_{flow}	flow rate [cfm or gph]
R_{gen}	generation rate [lb / hr]
S_{batch}	batch size [no. parts]; number of parts under operation simultaneously
$T_{depreciate}$	time to depreciate capital costs [yrs]
T_{proc}	processing time [min / part]
t	part feature tolerance [in. or mm]
V	voltage [V]

SUMMARY

Tolerancing decisions made in product design have a significant effect on manufacturing environmental and cost performances by strongly influencing both the selection and operation of processing machinery. These decisions however are typically made without quantitative knowledge of their effects in manufacturing. With estimates of environmental and cost performances of manufacturing processes required to achieve specific part designs earlier in the product design cycle, designers may make more informed, and potentially better, design decisions with respect to manufacturing environmental and cost performance goals.

In this thesis a method for quantifiably relating product tolerancing decisions to environmental and cost performances in manufacturing in order to provide decision support for cost and environmentally conscious design for manufacturing is developed. The method is instantiated as an Excel-based tool and exercised by two illustrative examples of increasing complexity, as well as a study of the manufacture of automotive transmission pinion gears with differing tolerance requirements. Uncertainty analysis is performed through the use of @RISK software; the uncertainty of parameters associated with manufacturing operations and machinery is captured through the use of probability density functions and Monte Carlo simulation is performed. Simulation results provide insight into the uncertainty of performance estimates and the risks associated with ensuing decision making.

This method may be useful to product designers, as well as process planners, to support decision making efforts related to cost and environmental consciousness in the

manufacturing phase of the product life cycle by offering the capabilities of generating predictive performance estimates of potential process plans, and also assessing performances of implemented manufacturing processes.

CHAPTER 1

INTRODUCTION

1.1 Objective of Thesis

The objective of this thesis is to develop a method for quantifiably relating product tolerancing decisions to environmental and cost performances in manufacturing, specifically to provide decision support for cost and environmentally conscious design for manufacturing.

1.2 Overview of the Problem

Many companies desire to be more environmentally friendly while also striving for cost competitiveness in the manufacture of their products. Geometric and dimensional tolerancing decisions made in product design contribute heavily to manufacturing environmental and cost performances by strongly influencing both the selection and operation of process machinery. These decisions however are typically made without quantitative knowledge of their effects in manufacturing.

Often internal and external customer demands on products will drive requirements for tighter geometric and dimensional tolerances, which are more expensive to achieve in manufacturing. An inherent conflict arises between meeting these customer demands and minimizing manufacturing costs (Huang, et al. 2005). In the context of product tolerancing decisions, product design engineers often lack rigorous understanding of this conflict, resulting in design decisions that are likely sub-optimal with respect to manufacturing cost and also environmental performance goals. In this situation, risk-averse approaches (i.e., averse to failing to satisfy customer demands) are frequently taken, but may yield product designs that are over-designed and more costly. Currently it is difficult to answer questions relating to how much more expensive these risk-averse designs are in terms of environmental and cost performances in manufacturing. In order to make efforts at improving the environmental and financial performances of a product in its manufacture through its design, better decision support that relates product design decisions to effects in manufacturing is needed.

1.3 Proposed Solution

In this thesis a method is developed to estimate environmental and cost performances of manufacturing processes selected to achieve part designs, in an effort to support cost and environmentally conscious design for manufacturing decision making. The uncertainty and variability inherent in manufacturing machinery and operations is captured through the use of probability density functions and Monte Carlo simulation is performed. Simulation results provide insight into the uncertainty of performance estimates and the risks associated with ensuing decision making. This method may be used by product designers, and process planners, to support decision making efforts related to cost and environmental consciousness in the manufacturing phase of the product life cycle.

This method is one of many necessary decision support tools to be used in concurrent, or integrated, environmentally conscious product design. In Figure 1, a map of concurrent and environmentally conscious design efforts is given; the method proposed in this thesis is but one aspect of this map. Concurrent engineering efforts attempt to consider all phases of the product life cycle simultaneously, from material acquisition, manufacture, distribution, service, and end-of-life disposition (Skalak 2002); integrating design across all life cycle phases requires the ability to predict each life cycle phase performance of proposed designs. Quantifiably connecting design decisions such as at the left hand side of Figure 1 to the relatively far away end effects on the right hand side of Figure 1 is necessary in order to rigorously consider those phase performances in upfront product design.

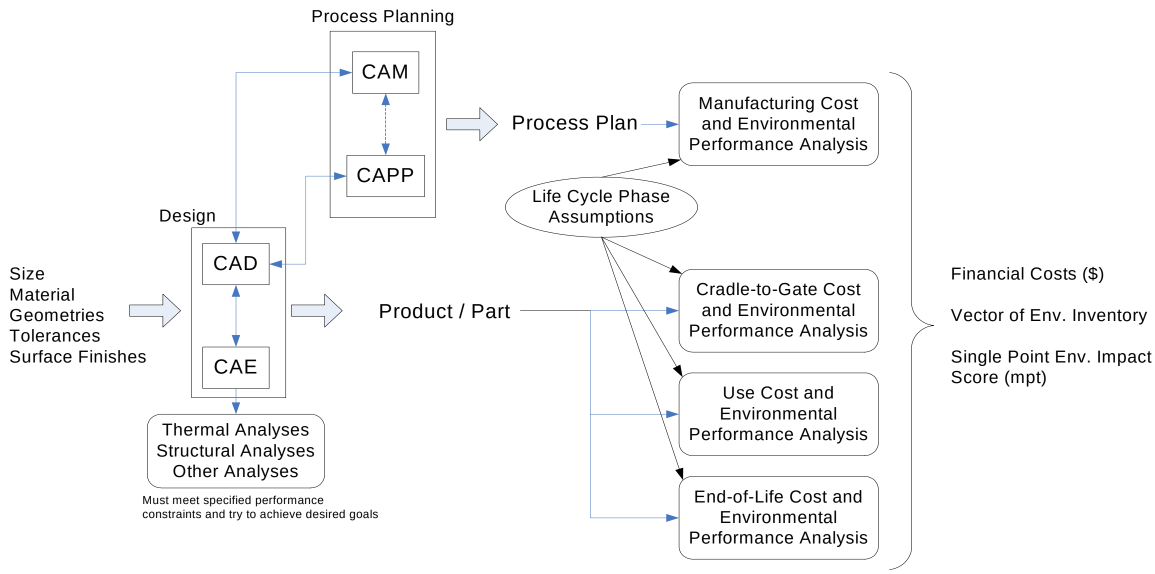

Figure 1 Map of Concurrent and Environmentally Conscious Design Efforts

In the design of a product and its process, designers and process planners strive to meet specified performance constraints while also trying to achieve desired goals. Tools such as Computer Aided Design (CAD), Computer Aided Engineering (CAE), Computer Aided Manufacturing (CAM), and Computer Aided Process Planning (CAPP) are widely employed to enable more integrated and efficient product realization. While CAE tools are primarily used to ensure functional performance of a product design in its use phase, and CAD/CAM/CAPP tools primarily used to improve manufacturability, other tools and methods are needed to consider other phases of the product life cycle. The method proposed in this thesis is concerned solely with the manufacturing phase; other methods / researchers have addressed cost and / or environmental concerns in other life cycle phases. This method, and others addressing different life cycle phases, are necessary to support tradeoff decisions across the life cycle.

Environmental concerns need to be considered as early in the design process as possible to better position the design for good environmental performance and not simply manage or quantify the "end of pipe" environmental impacts. But this action is not simple to do as Design for Environment (DfE) tools typically require substantial amounts of data and information that is simply not available or does not exist in the earliest phases of design. Due to the data intensity and workload required of certain DfE tools it is not possible or valuable to use them until a product design is fairly detailed, and potentially no longer flexible. This method attempts to address this situation through the use of reusable databases which contain the typical operating characteristics of machinery common to a particular company. Where identical production machinery is replicated or reused to produce other similar parts, perhaps of a part family, the usefulness of having these databases towards predicting future cost and environmental performances is very high.

The potential value and benefit of the proposed method that will be demonstrated in this thesis are, (1) the ability to accurately estimate manufacturing costs upfront, (2) providing more informed decision support with respect to environmental, in addition to cost, performances in manufacturing allows the opportunity to make better design decisions, and (3) putting high-level corporate environmental sustainability goals into day-to-day practice and reality.

More concrete metrics than vague statements such as "have good environmental performance" are available for use in the evaluation and selection of both product designs and process plans. If not better, more informed, decisions may be made with the estimates generated by this method.

1.4 Validation Square

After creating a method, it is important to assess its validity in order to help assess its applicability and usefulness. The Validation Square, proposed by Pederson, et al. (Pedersen, et al. 2000) is a tool that can guide the evaluation of the validity of a proposed method. It is pictured in Figure 2, and brief explanations of each region follow.

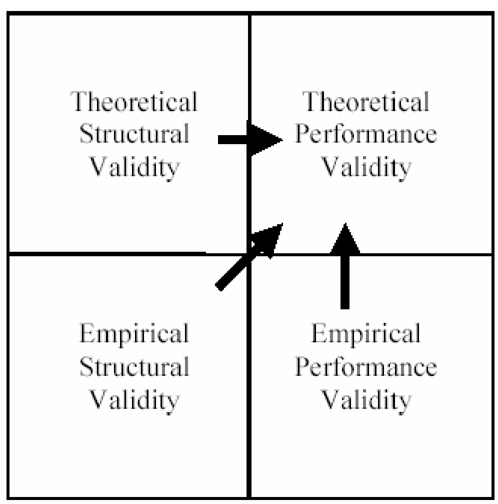

Figure 2 The Validation Square

Theoretical Structural Validity deals with the internal consistency of the design method and the constructs within it, and its logical soundness as a whole. Empirical

Structural Validity is the appropriateness of the example problems that have been used to test the method. Empirical Performance Validity is the ability of the method to produce appropriate results for the chosen example problems. The last region of the Validation Square is Theoretical Performance Validity, the ability for the method to produce results for applications beyond the chosen example problems. This last region cannot be proven explicitly or empirically; it must be assumed based on the success of the proposed method for each of the other regions and the method's ability to produce useful results over a broad range of applications.

The Validation Square will be used as the construct for examining the validity of the method proposed in this thesis. Testing the proposed method in each region of the Validation Square builds confidence in the method and allows a "leap of faith" made to Theoretical Performance Validity, the usefulness of this proposed method beyond the examples contained in this thesis. To satisfy each region, the designer of the method must successfully answer the following questions. For Theoretical Structural Validity (TSV), *Do each of the steps of the method make sense by themselves and do the steps fit together in a logical manner?* For Empirical Structural Validity (ESV), *Are the example problems appropriate?* For Empirical Performance Validity (EPV), *Are useful results realized for the example problem?* And lastly, for Theoretical Performance Validity (TPV), *Can useful results be realized for applications beyond the chosen example problem?*

1.5 Thesis Roadmap

After this introduction a literature review is conducted in Chapter 2 to establish the motivation for this work and identify the potential contributions to be made. The method structure and detailed workings are laid out in Chapters 3, and with Chapter 4 where the important role of databases is explained, Empirical Structural Validity is established. In Chapter 5, the instantiation of the method as a VBA-powered automated tool in Excel, coupled with @RISK software to perform uncertainty analyses is described. The Excel-based tool is exercised by two illustrative examples of increasing complexity in Chapter 6 as proof of concept and utility of the method, and to partially prove the Empirical Performance Validity of the method. A study of automotive transmission pinion gear manufacture, where gear tolerancing decisions have significant manufacturing environmental and cost performance implications, is conducted in Chapter 7 to give further evidence of Empirical Performance Validity. The thesis closes with a Critical Evaluation, of this work in Chapter 8, including a discussion of Theoretical Performance Validity, and a Closure with final remarks in Chapter 9.

CHAPTER 2

LITERATURE REVIEW

In this chapter the motivations for developing the method to relate product tolerancing decisions to environmental and cost performances in manufacturing are further established, and by examining the work of others the gap where this thesis may potentially make contributions is identified.

2.1 Design for Environment (DfE) Tools

Design may be thought of as a series of decisions that transform information from idea to reality (Tribus 1969, Sage 1977, Mistree, et al. 1990, Hazelrigg 1998). Computers and other tools can help (support) designers in their decision making activities and processes; in the realm of engineering it is desired to remove as much subjectivity as possible from the decision making process.

Many DfE tools exist to help designers lessen the environmental impacts of the products they design. The philosophy of evaluating a product in all the stages of its life cycle has arisen as the key way to not only quantify environmental impacts, but also to highlight opportunities for improvement. Looking at all life cycle stages is necessary since improvements in one life cycle stage may hurt environmental performance in others (Bras 1997). A commonly cited example from automobile design is using newer plastics or composite materials to make lightweight parts, which by reducing weight increases fuel economy during the use phase. However, many of these plastics or composites are not as readily or easily recyclable as the current metal parts, and would therefore increase the amount of end-of-life material sent to landfills in addition to requiring high levels of primary material content (Keoleian, et al. 2003). This type of tradeoff is not uncommon to all of the various life cycle approaches; tradeoffs in environmental impacts increase the complexity of a design where non-environmental tradeoffs, such as cost, performance, quality, etc., already exist (Handfield, et al. 2001).

A green design approach to product and process design attempts to reduce environmental impact without compromising a product's quality or commercial viability. DfE, similar to other Design for X (DfX, where X = assembly, manufacturing, recycling, etc.) approaches, may be defined as a philosophy that advocates that consideration be given to the environment when developing new products and processes. The most common tool involved in DfE is known as Life Cycle Analysis / Assessment (LCA) and exists as a number of variations. At the core, all are analytical tools that attempt to quantify and characterize the environmental burdens associated with a product life cycle, in the different phases from material extraction through retirement (Keoleian, et al. 2003); from "cradle to grave" or "womb to tomb". The environmental impact of a product is predominantly determined in its design phase (Handfield, et al. 2001); the materials used, the manufacturing processes, the effects of the product in use, and the product's final disposition, all of which contribute significantly to the product's overall environmental impact are set in stone by the design of the product.

Despite operational drawbacks of the formal LCAs (Krozer, et al. 1998), there are definite benefits to using LCA. It is a helpful tool for structuring discussions about environmental effects in product life cycles (Krozer, et al. 1998), and it is helpful in selecting the challenges and improvement options on which to focus (Graedel, et al. 1998). Though clear winning materials or processes might not result from an LCA all the impacts over the product's life cycle are visible, accessible, and quantified, and trade offs may be well, or at least better, understood. Full LCAs may be distilled down to a single score using some methods. The greatest benefit of using one of these single score methods to assess the environmental impact of a design is not dissimilar to LCA; designers are forced to look hard at the impacts of their designs in different life cycle stages.

2.2 Part Tolerances and Manufacturing Costs

According to the American Society of Mechanical Engineers, a tolerance is "the total permissible variation from design size, form, or location" (Kumar 1997) of a manufactured part and may be either parametric or geometric in form (Hong 2002). The parametric form is the conventional plus/minus method for assigning limits to part dimensions to define an allowable range (Hong 2002). Geometric tolerancing methods assign values to part features, such as profiles, locations, and orientations (Hong 2002). The tolerancing of parts is very important because specified tolerances impact a part's performance in both the manufacturing and use phases of its life cycle.

A design engineer is primarily concerned with achieving the required functionality of a product in its use phase at a minimum cost, though concurrent engineering efforts attempt to consider all phases of the products life cycle simultaneously, from material acquisition through end-of-life disposition (Skalak 2002). Specifying tight part feature tolerances often required for high performing, high quality products may be necessary for a product's functional performance in the use phase, but will not be beneficial for cost performance in the manufacturing phase.

All manufactured parts are subject to inherent variation associated with their manufacturing processes that leads to variability in the finished part (Fischer 2004). This variation is attributable to a number of sources, among others (Whybrew 1997):

- Machine factors: thermal stability, dynamic stiffness, geometric errors in the machine, resolution of the measuring and / or positioning systems;
- Cutting tool factors: thermal stability, tool wear, variation of tool size and cutting geometry, rigidity of tool and support,;
- Fixturing factors: thermal stability, variation in location, wear and contamination of locating surfaces, deflection of locators and fixture, variation between duplicate fixtures;
- Workpiece factors: thermal stability, variation in physical and chemical properties, rigidity of workpiece, stress relaxation, variation in workpiece size, part cleanliness;
- Coolant factors: variation of flow, variation of temperature, contamination, degradation;
- Operator factors: human error, variation of operator skill level and abilities
- Environmental Conditions: temperature, humidity, etc.

To achieve tighter product tolerance requirements necessitates sufficient or better control of the above process variables in order to reduce the variation of a manufacturing process (Ding 2000). Clearly, to control these numerous factors additional expenses will be added to a manufacturer. The additional expenses are attributable to the selection of more and sometimes additional precise machinery, tools, and fixtures, and more precise operation, monitoring, and control of the process. It is well understood in the literature and in industrial practice that tighter part tolerances are equivalent to higher costs in manufacturing (Kalpakjian 1997, Ding 2000, Huang, et al. 2005). Conversely, parts with looser tolerances and rougher finishes are more easily and less expensively produced due to reduced machining times, use of coarser tools, acceptance of greater process variation, reduced labor required for quality inspections, increased ease of measuring, and greater (potential) throughput.

The relationship between part tolerance levels and their associated manufacturing costs is commonly expressed as having the shape given in Figure 3 (Kalpakjian 1997, Sfantsikopoulos 1997, Whybrew 1997).

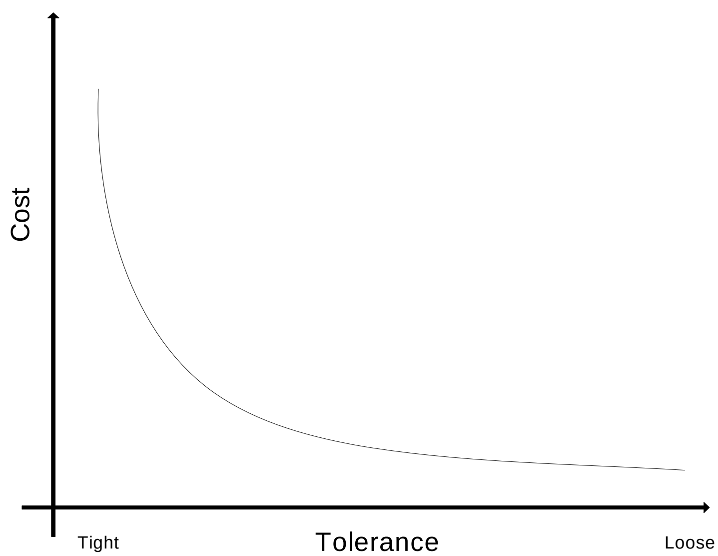

Figure 3 Typical Cost-Tolerance Curve

Manufacturing costs increase exponentially with the level of part tolerance that is specified and achieved in a part's manufacture. Many researchers have employed this knowledge of manufacturing costs in the form of cost-tolerance functions to specify or allocate part tolerances using optimization methods (Ngoi 1998, Ye 2003, Campatelli 2004, Huang, et al. 2005). These efforts attempt to minimize the manufacturing costs, while simultaneously minimizing a Taguchi quality loss function also dependent on product tolerance levels. Given that high quality, high performing products generally require tighter tolerances (Huang, et al. 2005), the Taguchi quality loss increases as product tolerances are made looser. Conversely, as product tolerances are tightened, the Taguchi quality loss is decreased. The cost-tolerance function and Taguchi quality loss function are in direct competition with each other. Minimizing quality loss will increase manufacturing costs while minimizing manufacturing costs will increase tolerances and thus quality cost. Applying a mathematical optimization routine or algorithm will find the “best” possible tolerance to satisfice (i.e., achieve a goal that is ‘good enough’ or satisfies the minimum requirements) these competing goal functions.

While cost-tolerance functions are powerful in their potential ability to optimally allocate product tolerances, these methods are not employed to a great degree in industry (Rush, et al. 2000, Hong 2002). The quantification of cost-tolerance relationships is incredibly difficult (Campatelli 2004), and explains the low rate of implementation in industry and the inability for designers to rigorously grasp this relationship.

With the derivation of detailed analytical expressions relating costs of manufacturing to dimensions and specified tolerance zones having been found to be extremely difficult, simple design rules and individual expertise are most used for ‘optimally’ tolerancing for costs (Sfantsikopoulos 1997). While this approach is useful, results from these methods are still likely sub-optimal as they rely on implicit human knowledge and decision making, and not science.

2.3 Predicting Manufacturing Costs

The desire to rigorously consider product manufacturing cost performance in upfront product design, particularly within concurrent and integrated design environments, is not new. Others have recognized that decisions made in the product design phase determine upwards of 70% to 80% of a product's realization cost, while the design phase itself only accounts for a small percentage of this realization cost (Ou-Yang, et al. 1997, Rehman, et al. 1998, Rush, et al. 2000, Shehab, et al. 2001, Layer, et al. 2002). The proportion contributions to product realization costs incurred and set (i.e., determined) in different product life cycle phases is given in Figure 4 from (Shehab, et al. 2001). An alternative perspective on this disproportionate situation, from (Rush, et al. 2000), is given in Figure 5. Also the costs associated with product use and end of life disposal are implicitly predetermined in product design (Layer, et al. 2002). Additionally, though the percentage contributions have not been expressed as for costs, decisions made in the product design phase establish the predominant life cycle environmental impacts of the product (Handfield, et al. 2001). Given the demonstrated significance and impact of decisions made in product design on manufacturing costs, it stands to reason that greater care should be taken in the design phase to consider potential downstream performance improvements and take advantage of the leverage held in the product design phase.

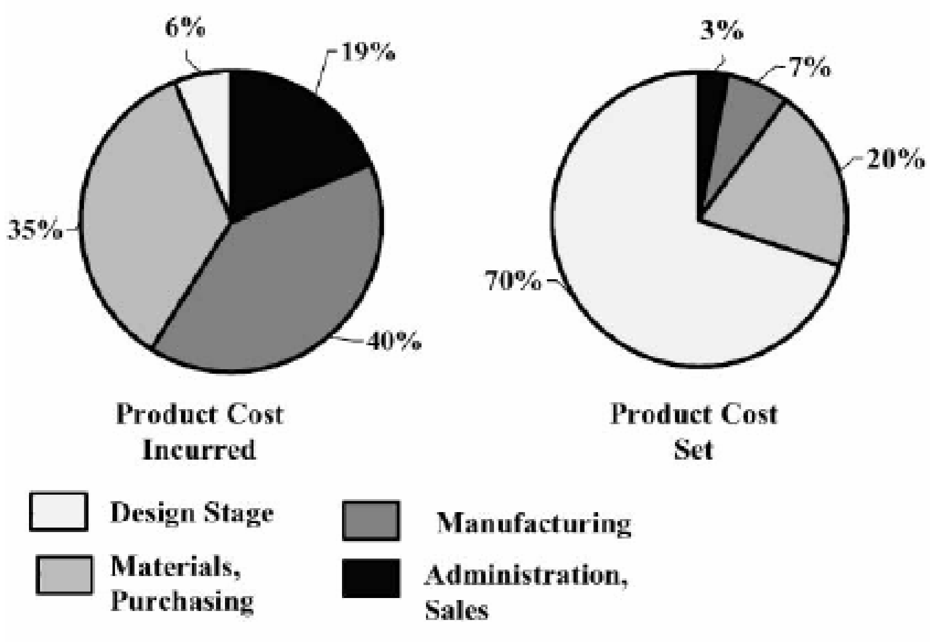

Figure 4 Product Costs Determined and Incurred in Different Product Life Cycle Phases, from (Shehab, et al. 2001)

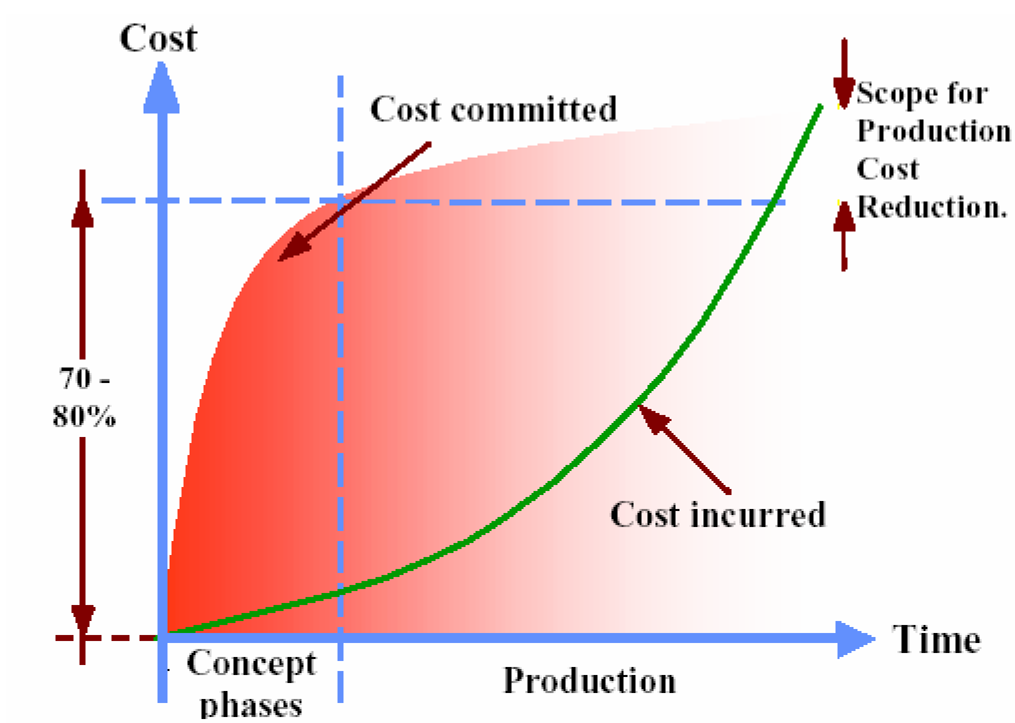

Figure 5 Cost Commitment Curve, from (Rush, et al. 2000)

Cost estimation should be used a decision support tool. Accurate estimates in early stages of product design are key because alterations and / or modifications to products and processes later in a development cycle are more expensive (Rush, et al. 2000), or impossible (Ou-Yang, et al. 1997). Cost as an evaluation criterion may be used in Design for Cost (DfC) or Design to Cost contexts (Shehab, et al. 2001). DfC, like other DfX methods involves the conscious inclusion of cost considerations in upfront product designs; the objectives of DfC are to (1) find aspects of a proposed design which may require high manufacturing cost, (2) provide a methodology for estimating the costs of design alternatives, and (3) reduce product life cycle costs (Ou-Yang, et al. 1997, Shehab, et al. 2001). Subtly different, Design to Cost aims to satisfy functional requirements of a product for a given cost target (Shehab, et al. 2001); in other words, the design must converge to a cost target, rather than the cost converging to a design (Rush, et al. 2000).

Conducting cost estimation, defined as "the art of approximating the probable worth or cost of an activity based on information available at the time" (Stewart 1991), for product manufacture at an early stage of design is not trivial. Some of the major requirements and / or difficulties to be addressed include:

- The need to show the derivation of cost estimates, including risks (i.e., uncertainty) and assumptions involved (Rush, et al. 2000);
- The need for accuracy in estimates (Rush, et al. 2000);
- The limited amounts of accurate data available for new products and processes (Rush, et al. 2000);

- Lack of detailed process plans, from which to base cost estimates, in the conceptual design phase (Rehman, et al. 1998).

Rush and Roy summarize several typical methods for estimating costs (Rush, et al. 2000):

- Use of past experiences with similar products and processes for early estimates;
- Use of Activity Based Costing (ABC) for more detailed estimation, which requires well understood product definition and is thus not suitable during early, conceptual design;
- Development of parametric cost estimating relationships (CER), similar to the cost-tolerance relationship presented in Figure 3 above. CERs however may be too simplistic however to accurately predict costs since manufacturing cost performance may not be simply attributable to a single product design parameter, such as weight or volume;
- Use of feature based costing (FBC) which appears to be fairly promising, though agreement on universal definitions of 'features' are lacking. A product may be considered as an assembly of a number of features, which will likely appear on many different components and products, and thus historical cost information related to product features may be used fairly often;
- Use of neural network based cost estimation, which employs artificial intelligence whereby computers learn relationships between design attributes and costs;
- Use of case-based reasoning (CBR), which uses analogy to similar products and tweaking for differences, but loses effectiveness similarly to neural networks when past cases are not available, such as for new, novel, and / or innovative designs.

Other methods for conducting cost estimation, with the intent for use in product design discussed by Rehman and Guenov (Rehman, et al. 1998):

- Application of empirically derived heuristics from many years of product realization experience;
- Use of knowledge-based expert systems, which rely on knowledge of design features in a design and attempt to automate a detailed process plan.

Many of the cost estimation procedures presented above involve the use of historical cost information stored in some type of database, but run into difficulties when faced with innovative products and processes. Though potentially powerful in the application towards accurately estimating and considering product manufacture costs in upfront design, most companies lack formal, disciplined procedures and approaches for costing in conceptual and detail design phases (Rush, et al. 2000). Instead, most rely primarily on expert (human) knowledge, "fraught with subjectivity" (Rush, et al. 2000). These methods also are limited in that other downstream life cycle phases are ignored.

2.3.1. Feature Based Costing

Since establishing a relationship between product tolerancing decisions and manufacturing performances is the objective of this thesis, parametric and feature based costing (FBC) methods discussed previously are the most appropriate for calculating estimates. Lacking specific historical information required to determine CERs, and wishing to develop a general method for generating manufacturing performance estimates given product feature tolerances, the work of others in feature based costing methods will be examined and discussed.

Ou-Yang and Lin (Ou-Yang, et al. 1997) developed an integrated framework for feature-based early manufacturing cost estimation. Their system tends to estimate cost performance of part manufacture by the shapes and precision of the design features, and is intended for fairly inexperienced designers who are typically unable to relate changes in shape, tolerances, and surface finishes to changes in manufacturing expenses. In their proposed, modified product development process, manufacturing cost estimation is moved up the chain, allowing for an iteration loop with the feature based part model design in a CAD system. In typical, traditional product development, manufacturing cost estimation does not occur until the part design is well defined and perhaps fixed in preparation for actual production.

The main components of their method framework are (1) a CAD system for constructing and modifying feature-based parts, (2) a reference library containing available machines with operation capabilities, costs, and surface finish ranges, and (3) an analysis module. In the reference library files is information on processing to make particular features with varying surface roughness, sequence and duration of processing steps, and costs for machine operations. The analysis module has two sub-modules; one extracts feature-based part information from the CAD system and includes features comprising the part, feature designs, and specified surface finishes for features. The other sub-module performs the cost analysis; this is completed by (1) analyzing the manufacturability of each feature by the precision capability / machining resolution of the processing equipment on the final step of each feature's creation, (2) estimating the required machining time of each feature based on the volume of material to be removed and required surface finish of the feature, and (3) computing cost using the estimated machining time of each processing step and the unit costs associated with each machine. Their framework for conducting feature-based cost estimation is given below in Figure 6.

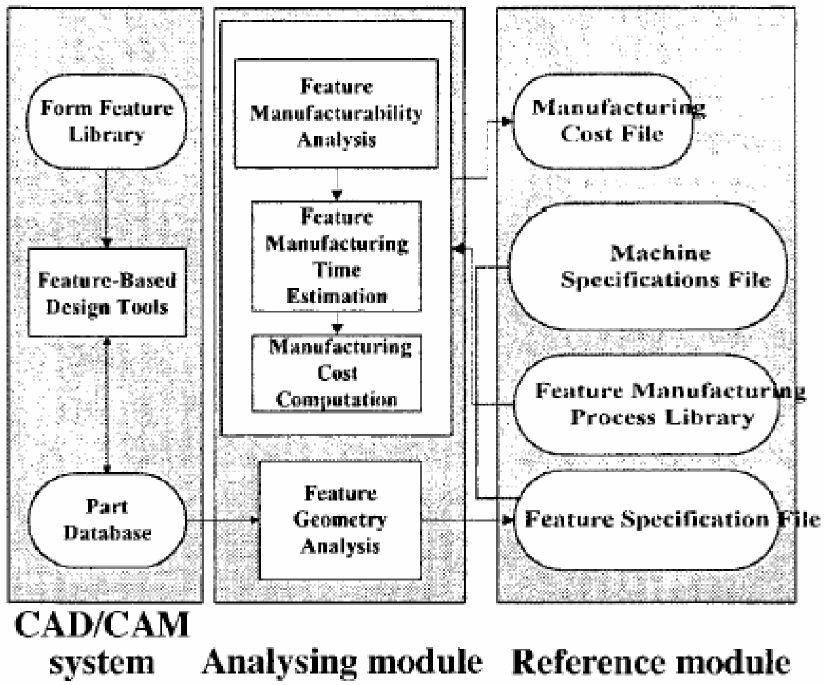

Figure 6 Framework for Cost Estimation, from (Ou-Yang, et al. 1997)

Ou-Yang and Lin's implementation of their method requires a designer to input the part model, constructed using features stored in a feature library, and then specifying appropriate design parameters and the desired surface roughness. The remaining steps of pulling information from reference library files, selecting machines for a proposed process, estimating machining time, and calculating estimates are automated by their tool. Their method and tool is not without its weaknesses. Feature dimensional tolerances and precision is not explicitly considered; their chosen precision parameter of interest is surface finish, which is somewhat related to tolerance but not exactly so. Additionally, the process planning step of their tool is completely automated; the situation whereby multiple machines are capable of achieving the specified surface finishes of part features is not addressed. Machine selection in this situation warrants discussion. Also, they admit issues with the validation of the correctness /accuracy of estimates obtained from this method, and the applicability of this method beyond machining processes. The strengths of their tool however are (1) the ability to highlight (potentially) overly expensive feature designs at an early enough stage that modifications to feature designs are still possible, (2) connection to a CAD system for part modeling, a tool many designers already commonly use, and (3) inclusion of an intelligent method of estimating machining times for use in the cost estimation sub-module. Given accurate cost and complete databases for a set of machines, this method is likely to give sufficiently good results.

Shehab and Abdalla (Shehab, et al. 2001) are others who have done similar work to Ou-Yang and Lin, but have also added a material selection component and expanded process planning to their proposed method. Their framework for conducting cost estimation is given below in Figure 7. A user creates a part in a feature-based CAD system, selects a material using Cambridge Material Selection software or by setting the material specifications manually, and conducts process planning steps. Material cost is added to the manufacturing cost and is a function of the volume of the part and material density and unit price. Process planning involves selection or generation of machining processes, their machining parameters, and their sequence. A knowledge base (i.e., a database) contains the specific machines required to create particular features with specified dimensional tolerances and surface finishes, and the costs to perform that operation. Additionally, a machinability database contains information on recommended machining parameters, such as feed rates and depths of cut, and is populated from handbooks. Machining time is computed identically to the method of Ou-Yang and Lin and used to compute manufacturing cost.

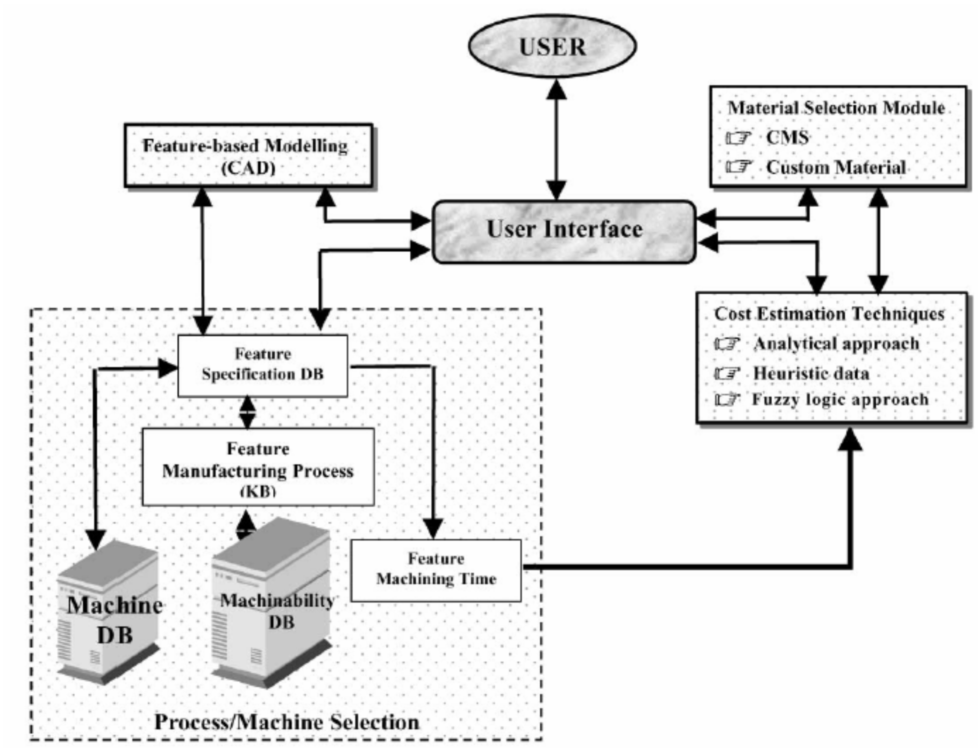

Figure 7 Architecture of Cost Estimation Model for Machining Processes, from (Shehab, et al. 2001)

A feature created in the CAD system is a generic shape which has product information such as tolerance and surface finish. Product features must match exactly the known manufacturing machine abilities. Feature definition is used directly in selecting both machining processes and their machining parameters, from which cost estimates are derived. Manufacturing knowledge is represented as production rules in the form of multiple IF … THEN statements, used to select machinery capable of producing a particular part with its unique feature designs. Set-up costs (e.g., adjusting tools, tweaking parameters such as speeds and feeds, and machine programming) and non-productive costs (e.g., load and unload times, indexing, and tool engagement) are recommended for inclusion; they should be added to the manufacturing and material costs already determined, and may be found in machining handbooks. Fuzzy logic is employed to handle the uncertainty involved in cost estimation.

The process planning in this method is again automated and one machine is picked that is capable of achieving the part feature designs. The benefits of this method, according to the authors, are similar to those of Ou-Yang and Lin's and are (1) the ability to estimate the cost of part manufacture at a sufficiently early time in design such that design modifications are possible, (2) identifying features that are difficult and costly to manufacture use the manufacturing resources known to be available, and (3) recommends the most economical machining processes, including order and machining parameters.

Both methods proposed by Ou-Yang and Lin, and Shehab and Abdalla have weaknesses; identified weaknesses are the following:

- The simplicity of the developed tools, and thus their likelihood of implementation in industry, is questionable; known CAD tools are utilized for part feature model creation, but the knowledge-base process generation system is not.
- The filling of databases of machine information (e.g., machinability, process capabilities, machining parameters, and cost performances) is not trivial as implied by these authors; for parts beyond the simple prismatic parts discussed as examples and case studies in both papers, with simple hole and slot features, specific and needed information may not exist to the degree desired in machine data handbooks. The

manufacturing knowledge of complex features and parts may require special collection and collating for entry into a database.

- Though Shehab and Abdalla's method included the use of fuzzy logic to incorporate the uncertainty associated with cost estimation, its impact on cost estimate results is not immediately clear; an output range or distribution is not reported or given. Thus, the inclusion of uncertainty and risk analysis of decision making supported by estimates generated by both methods is unsatisfactory.
- Both methods require some knowledge of historical cost information; this requirement is not likely to be able to disappear, but does hamper the methods' abilities to very accurately generate estimates for new, novel, or innovative product designs, which may use wholly unknown production machinery.
- Though likely useful in predicting manufacturing costs in high volume manufacturing environments, both methods appear more geared towards a machine shop environment, with a limited pool of production machinery, and smaller scales of production. An important consideration in high volume machining applications is the use of auxiliary equipment that supports the primary machinery producing parts. This auxiliary machinery, which may have substantial impact on cost performance, enables quality production and operation of primary machines, and protects workers in the manufacturing facility from potentially unhealthy or dangerous material by-products.

Layer, et al. point out several other weaknesses of the manufacturing cost estimation methods proposed by Ou-Yang and Lin, and others (Layer, et al. 2002):

- Lack of accuracy;

- Costs are determined in a lump-sum fashion and thus cost-driving product characteristics are not easily identified;
- Product design is only partially supported because only parts of manufacturing processes are considered, and increasing process plan definition is not used to update cost estimates from lower, initial estimates;
- Acquisition and maintenance of knowledge is difficult and conventional IT systems are not currently adequate for retrieving and storing manufacturing process information.

The biggest weakness, providing the greatest impetus and potential contribution of this work, is that neither method, nor any other methods found in the literature, consider the environmental performance of manufacturing processes required to achieve part feature designs, an important item of increasing concern.

2.4 The Environment as a Manufacturing Cost

The notion of manufacturing ‘costs’ should be expanded to include the environmental performance associated with manufacturing because of the deleterious effects on our environment that can no longer be ignored. The need to properly account for environmental performance in manufacturing is growing because: (1) companies must have ways of improving and controlling their environmental performances as environmental regulations around the globe become more encompassing and numerous (Graedel 1995), (2) while efforts to do good for the environment are noble and worthwhile, real progress is unknown without hard and reliable metrics, and (3) predicting it early in the design phase, when designs may still be modified, provides the greatest opportunities for making substantial life cycle environmental performance improvements. Interestingly, Pil and Rothenberg discuss how improving environmental performance in manufacturing may be shown to be both complementary to production quality improvements and as enabling of other types of manufacturing improvements (Pil, et al. 2003). In other words, improving environmental performance in manufacturing makes good business sense.

Additionally, while specific cost-tolerance relationships are difficult to determine, the relationship between manufacturing costs and products tolerances in Figure 3 has been well accepted. Currently, the relationship between part tolerances and manufacturing environmental performance is unknown. The manufacturing environmental performance-product tolerance curve may follow the cost-tolerance trend, but this shape has not yet been found.

With the motivations that (1) tolerancing decisions are made with significant lack of rigorous knowledge and understanding with respect to manufacturing 'costs'; (2) it is desired that environmental performance of a part's manufacture be factored into product design; and (3) ways for estimating environmental performance throughout product life cycles need further development and improvement; a structure for a method has been developed to improve the current state capabilities of designers and management towards these ends. This effort is a small step towards implementing corporate environmental sustainability goals into every day practice.

2.5 Thesis Roadmap

In this chapter the motivations for developing the method to relate product tolerancing decisions to environmental and cost performances in manufacturing have been further established, and by examining the work of others the gap where this thesis may potentially make contributions is identified. The motivations discussed were (1) the precedent of useful DfE tools for considering and improving environmental performances of products throughout the life cycle, (2) the strong impact of part tolerances on manufacturing performance, specifically costs, and lack of rigorous understanding in upfront product design, and (3) building on the work of others who have developed methods to predict manufacturing costs by expanding manufacturing performance estimates to include environmental considerations. Potential contributions of this work include connecting product tolerances to environmental and cost performance in manufacturing with a simple method, and the addition of the environmental dimension in predicting manufacturing 'costs'.

With the problem described, the motivation for this work established, and the potential contributions to be made identified, the method structure development is to be laid out in Chapters 3. Along with Chapter 4, where the important role of databases is explained, Empirical Structural Validity is established.

CHAPTER 3

DEVELOPMENT OF METHOD TO RELATE PRODUCT TOLERANCES TO MANUFACTURING PERFORMANCE

In this chapter development of the proposed method is discussed. The requirements for such a method to connect product tolerancing decisions to manufacturing environmental and cost performances are elucidated, the structure and implementation of the method that follow from the requirements of the method are explained, and the detailed workings of the front end process generation and back end process accounting, including mathematical modeling, ways to improve the accuracy of results, and the inclusion of uncertainty, are presented.

For use in product design a method which relates product tolerances to environmental and cost performances should be predictive; that is, with reasonable accuracy a product designer should be able to estimate the relatively far-away costs and environmental burdens associated with manufacturing his or her design. Other information that would be valuable to designers: (1) knowledge of how resulting costs and environmental burdens change as design values and parameters (e.g., tolerances) vary; and (2) knowledge of the specific tolerance levels above which resulting costs and environmental burdens are especially sensitive and elastic. This information may then be considered as criteria for making decisions related to the product's design. The weighting of the manufacturing cost and environmental burden criteria with respect to other design goals and requirements is left to the designer(s), management, and/or company policies, and is not prescribed here.

3.1 Requirements

Before jumping into the model development it is important to establish the requirements of the model similarly to the design methodology of Pahl and Beitz (Pahl, et al. 1996). The establishment of requirements or goals is useful for two reasons: (1) to guide and focus the development of the desired final result; and (2) to provide a useful metric by which to evaluate that final result. Formulating a requirements list is begun by posing a solution-neutral problem statement. For the development of this decision support method / tool, this solution-neutral problem statement is, "For a design tool to predict environmental burdens and costs (i.e., performance) in the manufacture of machined components, what features and abilities are needed / required?" Each item on the list is classified as a demand (D) or wish (W), indicating the relative priority for achievement. The requirements list for this method is presented in Figure 8, and brief explanations of each item on the list follow.

Problem Statement		
		For a design tool to predict environmental burdens and costs in the manufacture of machined components, what features and abilities are needed/required?
No.	D W	Requirements
		Accuracy
1	D	Provide reasonably accurate first pass environmental and cost information to support design decisions
2	W	Offer capability to input information to improve accuracy of results
3	D	Incorporate uncertainity of information and data and show uncertainty in output results
		Ease of Use
4	W	Do not add significant amounts of time or tasks to product designers' workload
		Flexibility
5	D	Be flexible to accommodate new or updated process information (e.g., machines, capabilities, operating characteristics, costs, by-products, utilities, etc.)

Figure 8 Method Requirements List

The requirements in Figure 8 for a predictive design tool were previously developed and elucidated in (Bradley, et al. 2006), but are further explained here. The first grouping of requirements is related to the need for estimates generated by the method to be accurate. Attempting to make decisions using inaccurate estimates is at best misleading, and at worst causes incorrect decision making with harmful effects on environmental and cost performances in manufacturing.

1. **Provide reasonably accurate first pass environmental and cost information to support design decisions**

In relatively early phases of product design, when process plans are not defined, the use of historical production machinery and process information may be used to generate initial manufacturing performance estimates. This first pass information will be useful in understanding the order of magnitude or ballpark of the 'costs' associated with particular designs, and highlight feature designs that are expensive, in terms of both the environment and financial costs.

2. **Offer capability to input information to improve accuracy of results**

As product and process designs progress, both become more well defined. With this increased definition, a better picture of the manufacturing process required to achieve the part design develops, and more representative information can be inputted to improve estimate accuracy. The first pass estimates derived from the historical information will be general and somewhat useful; however, specific process information for particular products, companies, or industries may be provided and inputted by the user to greatly improve the results for his or her particular situation. The models contained within the tool are quite simple and thus assumed to be valid themselves, so if the inputs into the model are accurate the estimates generated will be assumed to be accurate.

3. Incorporate uncertainty of information and data and show uncertainty in output results

Based on experience working with industry, the data and information required as inputs into the model for estimating cost and environmental performances are most likely not perfectly known; there will be some uncertainty about the data. Ignoring the uncertainty and computing the estimates in a deterministic fashion strips the user of the knowledge of the possible variability of those estimates and the risks involved with making decisions based on the results. The variation may be due to process variability itself, conflicting values for data from the vendor versus that which is internally acquired, and / or imprecise knowledge of the machine or process operation. A process is not strictly deterministic and some insight into the uncertainty of the results is necessary.

The product design community is 'under siege' with demands on them to achieve numerous design objectives simultaneously (Swarr 1999). This observation makes DfE initiatives difficult to realize in practice (Handfield, et al. 2001). Therefore any tool that supports DfE decision making should not burden the designer's who is attempting to use it. A tool that is inefficient, difficult to use, and / or has a steep learning curve most likely will not be used to the degree that is desired because of its burdensome use. A number of different characteristics for DfE tools have been identified in (Hrinyak, et al. 1996) and (VerGow, et al. 1994). The second category of requirements in the list is related to the necessity that a design tool be as easy to use as possible.

4. Do not add significant amounts of time or tasks to product designers' workload

In other words, the tool should be easy and efficient to use. If environmental performance is to be incorporated into the design of products, it must be considered alongside numerous other product design objectives; e.g., cost, manufacturability, reliability, quality, performance, testability, maintainability, etc. As is, the efforts to put forth product designs that satisfy those numerous objectives are substantial; that is, accomplishing these tasks is far from trivial and requires significant time investments. Additionally, pressures to reduce design cycle times in order to bring products to market faster further compound the difficulties faced by product designers.

The final category of requirements in the list is related to flexibility, which includes customizability.

5. Be flexible to accommodate new or updated process information

Different processes may use different utilities and / or generate different by-products; a user must be able to add specific environmental burdens of interest. Additionally, process characteristics such as processing times, operating costs, and environmental burden rates, change with the implementation of new technologies, improved efficiencies, upgrades, cost inflation and fluctuations, and between machine manufacturers. A user wishing to more accurately model processes specific to his or her part(s), company, or industry needs the ability input the 'best' available information.

3.1.1. Impact of Requirements on Method

The requirements given above will guide the development of the proposed design tool, and provide suitable metrics for evaluating the developed method. In Figure 9 the impacts on the design tool of the stated requirements are given, and brief discussion on each impact follows.

	Method Requirements	Impact on Design Tool
1	Provide reasonably accurate first pass environmental and cost information to support design decisions	Use (historical) information stored in databases
2	Offer capability to input information to improve accuracy of results	Allow users to "twist the knobs" of models in tool, and update databases
3	Incorporate uncertainity of information and data and show uncertainty in output results	Model uncertain inputs with probability density functions, perform Monte Carlo simulations
4	Do not add significant amounts of time or tasks to product designers' workload	Implement on a computer; automate as much of tool as possible with coding; use relatively simple and common software
5	Be flexible to accommodate new or updated process information (e.g., machines, capabilities, operating characteristics, costs, by-products, utilities, etc.)	Do not hard-code dimensions of databases: attributes, slots, and instances

Figure 9 Impact of Requirements on Design Tool

1. Use of (historical) information in databases.

Information from previous, and similar, manufacturing operations will be used as a baseline for predicting environmental and cost performance estimates. This information will be housed in databases from which it may be extracted as needed for calculations.

2. **Allow users to "twist the knobs" of models in the tool, and update databases**.

The inputs that drive performance estimation should be highlighted and accessible for tweaking, 'twisting the knob' so to speak such that the (proposed) manufacturing process is properly modeled. Additionally, the databases from which needed values are extracted should be accessible and updatable as more accurate / relevant machinery and process information/data becomes available or is developed.

3. **Model uncertain inputs with probability density functions, perform Monte Carlo simulations.**

This will be accomplished using @RISK software (or similar such as Crystal Ball). This particular type of software allows for the assignment of distribution information to parameters within an Excel-based model. The simulation involves running the model hundreds of times and sampling parameter values within their defined distributions and computing the output results. The result of the simulation is a distribution with an average value and some shape or spread. This type of result is more insightful, and accurate in terms of representing reality, than a simple, single point result (such as an average or nominal value) as they have incorporated the uncertainty of parameters directly into the model, and thus show the resulting variability of the output.

4. **Implement on a computer; automate as much of tool as possible with coding; use relatively simple and common software.**

Computers are powerful tools that can extend the abilities of humans exponentially. Implementing a design tool on a computer allows for rapid computation and execution of the tool, along with the upkeep and utilization of a dynamic database of process information. Microsoft Excel is chosen due to its prevalence and ease of use for a potential product design user. Additionally, the fairly straightforward coding of macros in Visual Basic allows for the automation of numerous aspects of the proposed method, meaning less effort required on the part of the user.

5. Do not hard-code dimensions of databases: attributes, slots, and instances

Having a degree of openness and flexibility is very important to robustly account for potential future unknowns for which the tool may have to account. This flexibility may be realized by not hard-coding the number of possible attributes (e.g., environmental burden rates, cost rates, etc.), slots, and instances of particular items in the databases.

With requirements and their effects on the method development spelled out, the structure of the developed method warrants discussion.

3.2 Overview of Structure

There are two primary groups of users who will interact with the method: product and process designers and process engineers. Product and process designers (i.e., product designers and process planners) will utilize the method to estimate manufacturing performances of potential product and process designs. Process engineers, and other manufacturing operations personnel, will be the knowledge source for many of the required informational inputs to the method. The motivation for process engineers to provide information and support to this method is to make their jobs easier in future manufacturing operations by enabling product and process designers to design products and processes which have considered manufacturing performances upfront.

A high-level overview of the method is shown below in Figure 10. At the top of Figure 10 a designer would input the dimensions and tolerances specified for particular part features (e.g., hole location, depth, and diameter). The part of the method enclosed in the dashed box is hidden from, though still accessible by, the user. In this box is the 'behind the scenes' information required to compute the environmental and cost performances of a manufacturing process. These hidden inputs may be updated and custom tailored as needed, but a product design engineer most likely should not be tasked with doing so, unless he or she is quite knowledgeable of the manufacturing operations.

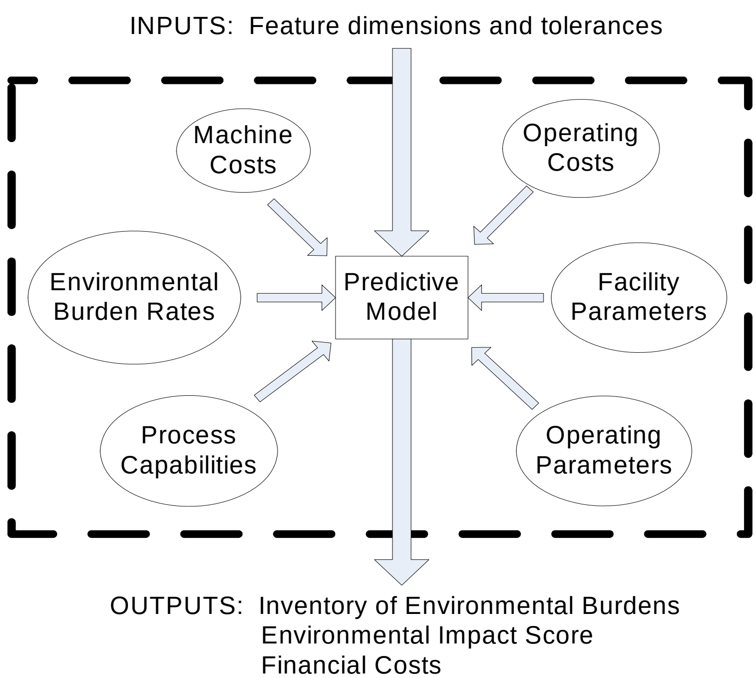

Figure 10 Predictive Model Inputs and Outputs

At the bottom of Figure 10, the outputs from the method are indicators of cost and environmental performances in manufacturing: the inventory of individual environmental burdens (also called loads), an environmental impact score, and the financial costs. Environmental burdens and financial costs are comprised of the following:

- Environmental Burdens: energy (e.g., electricity, compressed air, steam, and natural gas), water use, and by-products (e.g., CO_2, landfillable and hazardous wastes, and recyclable materials);
- Financial Costs: tooling, consumables (e.g., filters and fluids), acquisition (i.e., initial machinery purchase), direct labor, utilities usage, and by-products disposition.

Environmental impacts may be converted from an inventory of environmental burdens through the use of indicators, such as Eco-indicator 99, which allows the calculation of a cumulative environmental single point score (*SPS*) (Goedkoop 2001). Thus the useful outputs for a product designer, which could be factored into design decision making are the environmental burden inventory, the environmental impact single point score, and the cumulative financial costs.

A single score method for environmental impact attempts to distill a full life cycle assessment / analysis (LCA) into a single, numerical result whereby comparisons between alternatives, be it materials, designs, or processes, may be quickly and easily made. This method creates an inventory and values the results based on indices assigned to materials; from these values for each part of the product life cycle an overall index is calculated. A smaller single point score is indicative of lesser environmental harm over the life cycle.

There are drawbacks to a single score method, but also some benefits. The main drawback is the lack of transparency; there is a lack of sufficient detail to help decision makers understand the significance of a particular environmental score. Designers are unable to communicate trade offs because they are hidden behind the score, and comparing detailed results is simply not possible (Sullivan, et al. 1998). Single score results do not capture complex system impacts on the environment. The key benefit however is to provide a quick indicator of life cycle environmental performance that is perhaps more useful when comparing alternatives, than stand alone values.

Reconfiguring Figure 10 to show the desired inputs and outputs of the tool, from the perspective of a user in product design, Figure 11 is presented. The items contained in the dashed box of Figure 10 are wrapped and not visible. A method that is able to achieve the desired functionality of Figure 11, that is, the only input required of the product design user is the design of the part of interest to estimate manufacturing performances, would be helpful towards meeting the requirement that the method not be burdensome to its user. This may be accomplished by automating calculations and using existing, past information on the manufacture of similar parts.

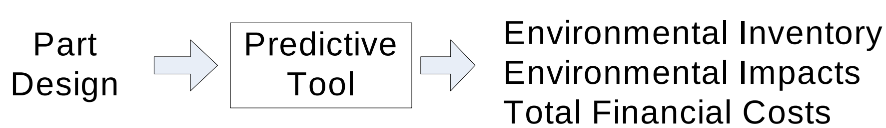

Figure 11 Desired Inputs and Outputs of Tool

Delving into the solid box of Figure 11 (the dashed box of Figure 10), is the domain of more advanced users conducting more advanced and complex analyses. Performing these advanced acts is not likely possible until further along in the design phase when the product design and its process plan are better defined. This ability is helpful towards meeting the requirement that the accuracy of estimates may be improved.

Breaking Figures 10 and 11 down and developing a method or procedure of conducting the required analysis is presented in Figure 12. This structure is broken down into two sections: a front end where potential processes are generated, and a back end where process characteristics are calculated and accounted. The dashed vertical line in Figure 12 marks the boundary between these two sections; the details on the specific workings of each will be examined in detail in the next sections.

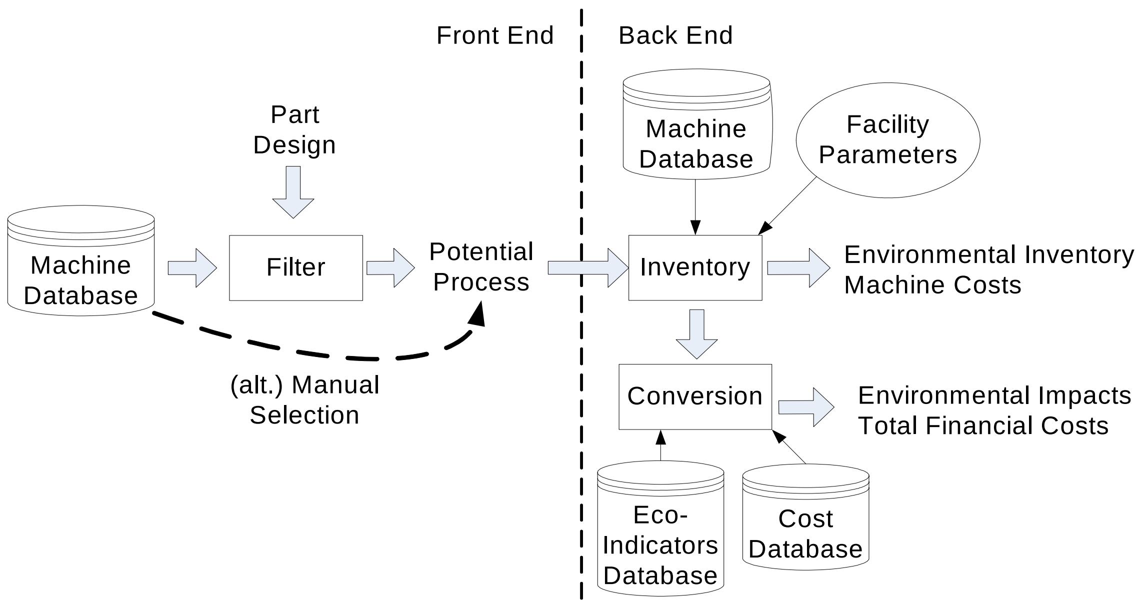

Figure 12 Overall Structure of Method

The use of dynamic databases (knowledge bases / repositories) addresses the requirements that the method (attempt to) provide reasonably accurate estimates by storing historical information, allow for flexibility and improvements in accuracy by providing the means to input new and / or additional information, and lastly incorporate uncertainty by storing uncertainty representations / models in the databases for inclusion in computations.

3.3 Front End, Process Generation

In order to understand how process plans can be generated from a part design, an understanding of how process planning works is needed. Process planning has been called the "integration link between design and manufacturing" (Singh 1996) and in essence is the product development activity that determines how a part will be manufactured. Process planning is carried out at a high level in the design of manufacturing production lines, and also at a detailed level in the setting up of individual operations on a production line. Traditional machining process planning can be carried out either manually or with the assistance of computer aided process planning (CAPP) systems (Chang 1998). Obviously, using CAPP systems has many advantages over manual process planning such as reduced process planning time and manufacturing cost, and creation of more consistent process plans (Chang 1998). For these reasons, in 1996, Singh stated that more companies were moving towards adopting CAPP systems (Singh 1996), even though in 1998, Chang and coauthors stated that most process plans were still prepared manually (Chang 1998). Therefore, both must be addressed.

For machining, two main CAPP approaches have been suggested: variant and generative (Singh 1996, Chang 1998). Variant approaches work by identifying, retrieving and modifying existing process plans (Chang 1998). Generative approaches generate process plans via the use of a feature-based or geometry-based coding scheme and manufacturing process knowledge (Chang 1998). While some researchers have stated that generative feature-based CAPP is the dominant model for CAPP research (Mukerjee 1997), other researchers have stated that in practice, variant approaches support almost all use of CAPP approaches (Elinson 1997).

Manual approaches could be facilitated by using company-specific process planning procedures based on “best practice” knowledge attained from years of experience in manufacturing given types of parts. This knowledge could lead to standard process plans with limited amounts of built-in flexibility to accommodate changes in certain design features.

Before estimating the performance of part manufacture, the manufacturing process must first be established. The key idea is to convert product designs to process plans via the capabilities of machines create features and achieve required production volumes / rates. The method employs a mix of generative, feature-based and variant process planning to generate the processes necessary to achieve the inputted part design. The front end section of the method, taken from Figure 12, which is a simplified representation of the method’s operation, is shown in Figure 13.

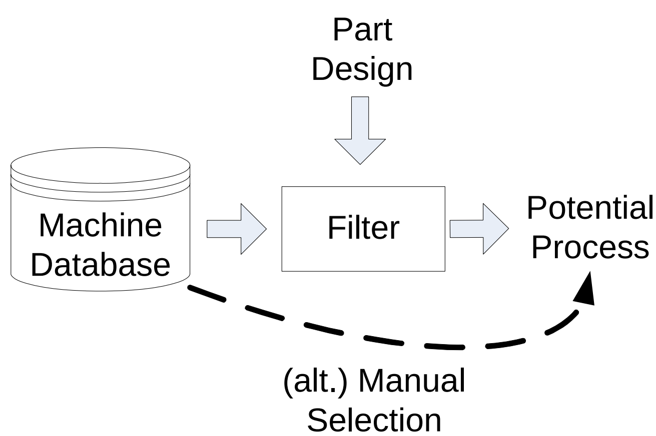

Figure 13 Simplified Front End Process Generation

The path in Figure 13 that goes through the Filter operation to determine a potential process to achieve the inputted part design is an example of conducting feature-based process planning; machines are selected based on their ability to successfully create feature designs. The essence of the filter is the use of if…then production rules, also used by Shehab and Abdalla in their method for predicting manufacturing costs (Shehab, et al. 2001). The alternative to using the feature-based approach of the filter is to manually select machines from the machine database and perform a kind of variant process planning. The potential process that is generated in the front end is comprised of both primary and auxiliary production machinery or equipment. Primary machinery is that which operates directly on the parts being produced while auxiliary machinery is that which supports the main (primary) processing steps of part's manufacture but is not directly involved in creating the part itself. Examples of primary and auxiliary machinery are milling machines and mist collectors, respectively. The selection of these machines and assembly into a potential manufacturing process is a bit more complicated than the simplified overview given in Figure 13. The schematic of the full front end process generation is given below in Figure 14.

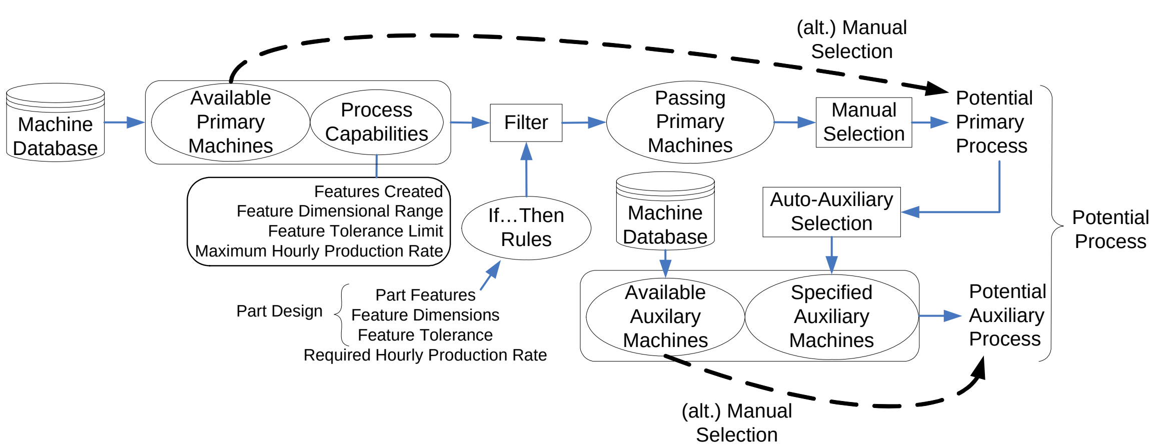

Figure 14 Schematic of Front End Process Generation

3.3.1 Filtering of Primary Machines

A part design (i.e., part features, feature dimensions and tolerances) in addition to required hourly production rate is the main input required from the tool user; this information is shown in the lower left hand portion of Figure 14. This part design information is used as decision criteria in if…then production rules utilized in the Filter operation. The process capabilities, consisting of feature type capability, feature dimensional range and tolerance limit, and the maximum hourly production rate, of each available primary machine, stored in a database of primary machines, are used to filter out those machines that are incapable of achieving the required part feature designs. The filtering of primary machines is conducted using the simplified logic of the algorithm shown in Figure 15.

For Machine_i, i = 1 to N (where N is the total number of available primary machines in the database)

If *design feature type* is a *feature created by machine* Then;

If *machine feature dimension LB* ≤ *design feature dimension* ≤ *machine feature dimension UB* Then;

If *design feature tolerance* ≥ *machine feature tolerance limit* Then;

If *required hourly production* ≤ *machine maximum hourly production* Then;

Machine_i is a Passing Primary Machine, add to list of passing machines;

Go to next machine

END

Figure 15 If…Then Primary Machine Filtering Algorithm

For any machine whose process capabilities do not pass an if statement, the primary machine is rejected (i.e., not included as 'passing') and the next machine is evaluated. For machines capable of creating multiple feature types, the selection of the machine is an AND operation, as opposed to an OR operation. To 'pass' and be returned, a machine must be able to successfully create *all* of its capable features on the inputted design. This does not mean however that one machine must be able to create all of the features of the inputted design.

Once all available machines have been evaluated and capable machines passing through the filter, the user must select the desired machines to compose the potential primary process. This additional instance of manual input is necessary to account for those situations when more than one primary machine is capable of producing the same feature design.

3.3.1.1 Discussion on the Filtering of Primary Machines

The filtering operation implemented as the tool discussed in Chapter 5 currently can not handle parts with more than one design of a feature type (e.g., a part with multiple holes, each with a different diameter, depth, and tolerances). The current coding will only consider the last entry of a feature type design in determining 'passing' primary machines. Despite this limitation, the auto-filter method may still be employed to carry out feature based process planning. Each unique design of a feature type may be inputted individually, the auto-filter run, and the passing machines recorded. The desired primary machines for each part feature should be noted and the process generated by selecting the passing machines from a listing of all primary machines; this method of variant process planning is discussed in the next section as an alternative method to generate the proposed process plan to achieve the inputted part design.

The benefit of this method is the ability to directly link machines to specific features. With multiples of the same feature type, and not simply duplicates of the same feature design, important process planning considerations, with respect to likely increases in both manufacturing costs and environmental impacts, are (1) the possible addition of a primary machine to perform the additional feature creating operation, or (2) having a flexible, and perhaps multi-stage, primary machine that is able to successfully create all of the specified features.

Primary machines that do not directly create feature dimensions and / or tolerances, but play critical roles in the manufacturing process, such as cleaning machines and heat treatment furnaces, need to be manually added to the potential primary process as they are not automatically returned by this method.

3.3.2 Generating the Auxiliary Process Automatically

After selecting the primary machines to be used in the potential process, the auxiliary machines to support those primary machines in the process needs to be generated. Auxiliary machines can be listed in the primary machine database as required for a primary machine. For example, for many dry cutting operations in a high volume manufacturing environment, a dust collector is required as an auxiliary machine to support the primary operation of dry cutting. The Auto-Auxiliary Selection operation shown in Figure 14 returns those auxiliary machines specified as required by the chosen primary machines in the potential primary process. Machines that are not automatically returned may also be manually inputted if needed.

3.3.3 Variant Process Planning by Manual Selection

Alternatives to the feature-based process planning method by filtering for the potential primary process, and the auto-selection for the potential auxiliary process, just presented above is to use variant process planning. This method may be used when either specific feature information (i.e., dimensions and tolerances) is not known for the part design or the primary machinery in the database, the required auxiliary machines for primary machines are not specified in the primary machine database, and / or the manufacturing process for a given part is defined by a common or best practice. This method may be used when, and / or the auxiliary process for a given part is defined by a common or best practice. Using this method ignores any feature design information that may be known or inputted and the auxiliary machine requirements in the primary machine database for those machines selected for the potential primary process. Machine selection is solely up to the decision of the user who must manually make selections. This alternative, manual selection action is pictured in Figure 14 as the heavy dashed arrows that go from available machines in the database to the potential process, for both primary and auxiliary process, and thus by-pass the filtering and auto-selection functions.

3.3.4 Alternative Methods for Generating Processes

There are alternative methods external to the front end process generation, as discussed in the preceding sections, to determine the primary and auxiliary processes for a proposed manufacturing process. The process capabilities of primary machines are the most important link in the filtering process of the front end and they will be discussed further in Chapter 4, as they have an important role in the database of primary machines. A limitation or difficulty to be encountered with this technique however is the requirement for process capability information to be known explicitly for both the part feature dimensions and tolerances. Especially related to feature tolerances, this process capability information may not be known at an early product design phase, and in fact may not be truly known until empirically determined on already implemented processes. To circumvent or alleviate this problem, approaches to process generation, external to the method proposed in this thesis, are discussed next.

There exist commercially available softwares, such as eFactory, for carrying out Computer Aided Process Planning (CAPP) and Computer Aided Manufacturing (CAM). These softwares similarly attempt to automate process planning (i.e., process design or generation); a part design is inputted as a 3D CAD model and a potential process for manufacturing the part is proposed. Currently CAPP softwares are generally only relevant for traditional machining processes. They may offer the ability and detail to optimize tool paths for cutting operations, but will leave out cleaning and / or auxiliary operations that can have very significant impacts on cost and environmental performances in manufacturing. Auxiliary operations are operations that support the main processing steps of part's manufacture but are not directly involved in creating the part itself. An example of an auxiliary process is a coolant system that filters and circulates cutting fluid to multiple cutting machines in a high volume manufacturing environment.

Another alternative approach to process generation is the use of best practices or standards, which may be unique to either an industry or individual companies. A best practice is generally developed through years of experience and is a company's 'recipe' for manufacturing particular parts or components (e.g., transmission gears). Establishing a standard greatly simplifies process planning as the choices and combination of possible operations and processing order has been greatly reduced. For a particular part design, a process planner will tweak the standard manufacturing process as needed, based on part design parameters such as tolerances and surface finish and manufacturability requirements.

3.3.5 Discussion of Front End Process Generation

The process planning conducted in the front end of this proposed method is admittedly simplistic. The design of manufacturing processes to produce quality parts in a reliable, repeatable manner at required production levels, with considerations to a host of cost, business, and facility issues, is not trivial. Keeping in mind that the goal of this method is to be used in product design to support cost and environmentally conscious design for manufacturing decision making, and not as a CAPP system, the full spectrum of process planning is not considered. Process planning may be considered to occur at two levels: selection and then compromise. The two parts of selection involved in manufacturing process planning are depicted in Figures 16 and 17, respectively.

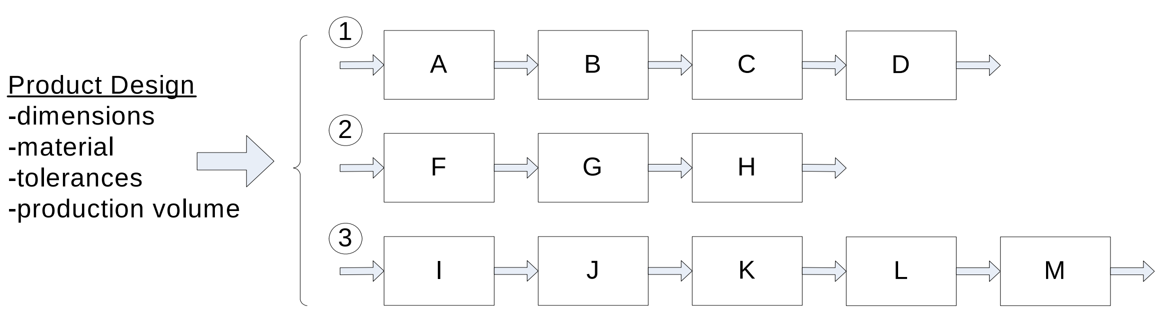

Figure 16 Selection in Process Planning, Part 1

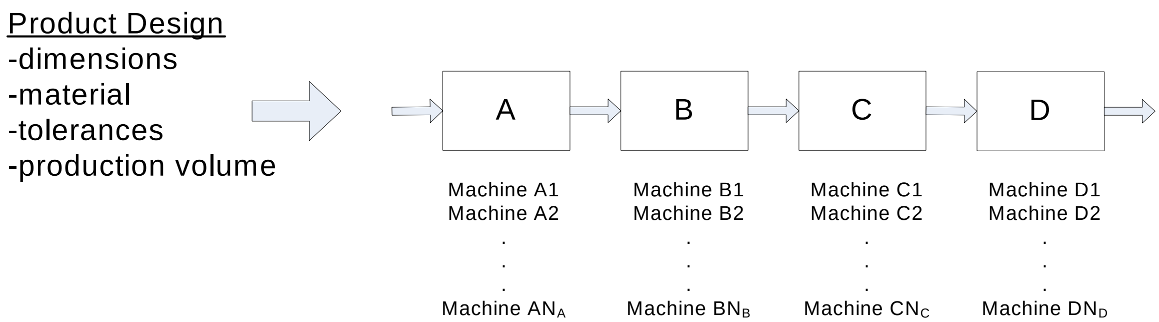

Figure 17 Selection in Process Planning, Part 2

The first part of selection in process planning, shown in Figure 16, as the name implies involves the selection of the process to be used to successfully produce the part design. In Figure 16, three different production lines (processes / methods) are given as alternatives for producing the part design at the left hand side. The first task in process planning is thus to select from the possible processing methods the one to be used to produce the part design. Once this is accomplished, the particular machines to be used in the chosen process must be selected; this second part of selection in process planning is shown in Figure 17. Machines offered by competing vendors and manufacturers are considered, though the machine selection is typically made as a business decision; previous experience, known quality, and service and support relationships are important considerations. Following both aspects of selection in process planning is the compromise operation; depicted in Figure 18.

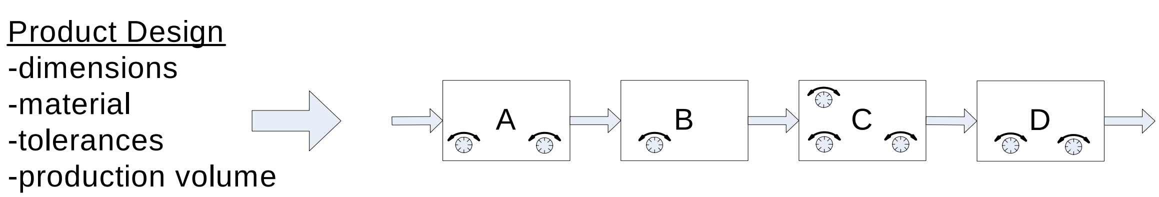

Figure 18 Compromise in Process Planning

The compromise step in process planning occurs once the process type and the particular machines in that process are set, and involves the adjustment / tweaking of the machine parameters to satisfactorily produce the part design. These adjustments to the production machinery are shown in Figure 18 as knobs that may be turned and thus set the necessary machine parameters. Some of the parameters requiring adjustment are depths of cut, feed rates, coolant flow rates, tool speeds, batch sizes, and cutting paths. The decisions made in this compromise portion of process planning will have impacts on the manufacturing performance, but it is not explicitly considered in this method. This step is not included due to (1) its inherent difficulty and complexity to automate, and (2) the role of mass and energy balances of inputs and outputs to each machine as the chief concern for environmental performance estimation. Detailed workings of machine operation are abstracted into a machine-level processing time, which is then used to attribute per unit of product performance estimates. Internal processing flow and mechanics of the operation are treated as a black box. Though not automated in this method, the ability to manually consider these compromise decisions exists.

Currently more of an art than a science, process planning requires substantial human knowledge, expertise, and experience to conduct. Once a potential process is generated though, regardless of generation method, it is relatively straightforward to 'pull' information on specific machines from a database in order to use it to estimate the cost and environmental performances of the potential process.

3.4 Back End, Process Accounting

With a potential process, which includes primary and auxiliary machinery, generated and outputted from the front end of the method, that process may be accounted and cost and environmental performance estimates made. The steps in the back end of the model are the creation of an inventory of environmental burdens and determination of traditional machine costs, followed by a conversion step whereby inventory items are converted to costs and environmental impacts. Specific machine information stored in the machine database, coupled with facility parameters and Eco-indicator and costs databases, is used in these steps to perform the calculations. The key idea is to use typical characteristics of machines in the primary and auxiliary processes to predict aggregate environmental and cost performances. The back end section of the method, taken from Figure 12, which is a simplified representation of the method's operation, is shown in Figure 19.

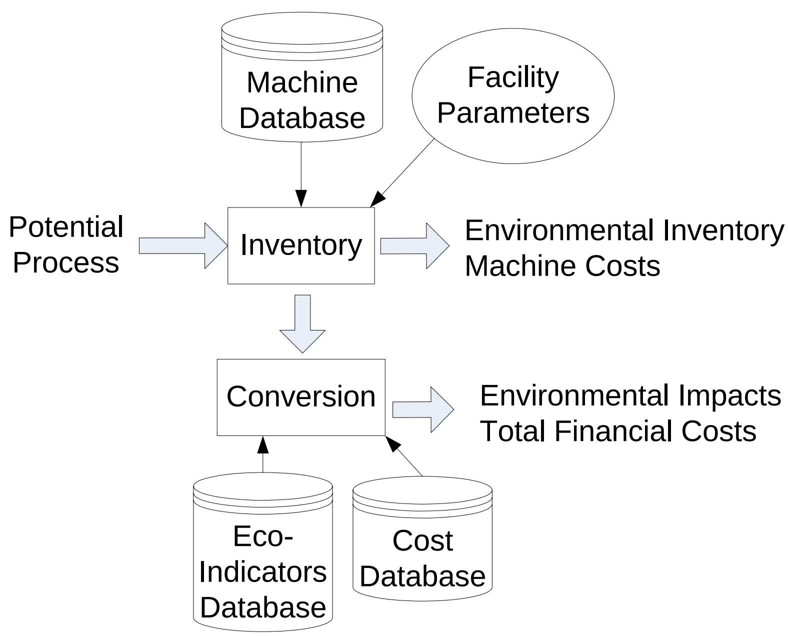

Figure 19 Simplified Back End Process Accounting

The back end operation is simpler than that of the front end, but is somewhat more involved than Figure 19 shows. The primary and auxiliary machines of potential process inputted into the back end have their information pulled from the machine database, and using mathematical models (discussed later in this Section), coupled with additional facility parameters, environmental burdens and traditional machine costs estimated in the Inventory step shown in Figure 19. The specific information pulled for each machine is the environmental burden rates consisting of the utilities usages and by-product generation rates, machine costs consisting of acquisition and yearly tooling and consumables costs, and typical operating parameters of batch size and processing times. Along with facility parameters of working hours and number of operators for the production line, this machine information provides the inputs to the mathematical models that calculate the traditional machine costs, direct labor, and the inventory of environmental burdens. This inventory of environmental burdens may be of interest to users of the tool as an output because it contains information in units of measure that may be more understandable and transparent versus an aggregate *SPS* and its units of millipoints (Sullivan, et al. 1998).

The Conversion step in Figure 19 does exactly that, it converts utility and by-product items in the inventory into environmental impacts and financial costs. Conversion is accomplished using EI-99 values and cost rates contained in databases. The environmental impacts are summed to create a single point environmental impact score, and the utility and by-products costs added to the traditional machine costs and labor to create the total financial cost. The schematic of the back front end process accounting is given below in Figure 20.

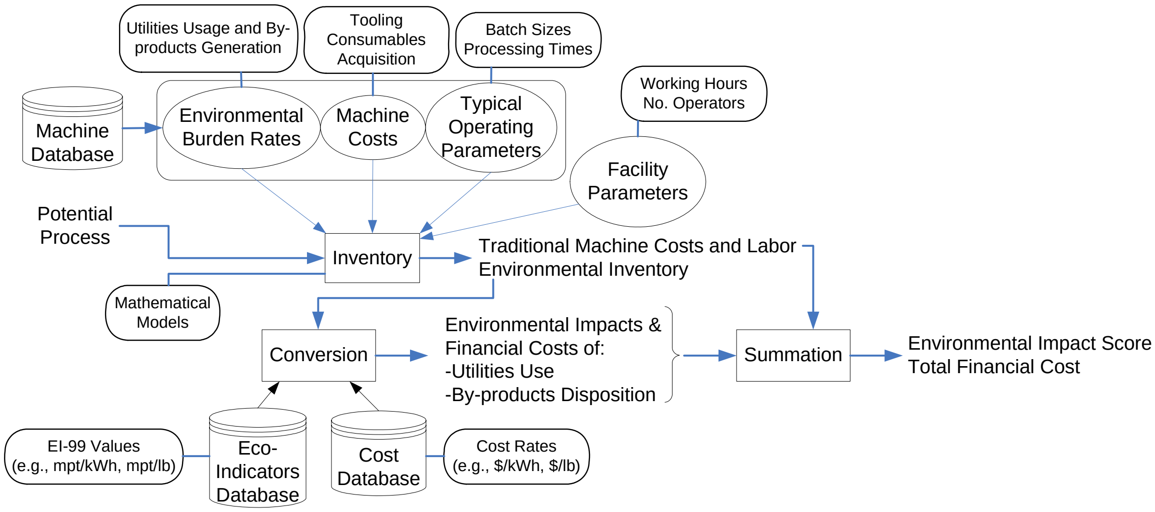

Figure 20 Schematic for Back End Process Accounting

Using the expanded definition of cost to include environmental impacts, a 'total' cost as reported as the output of the proposed method may be defined as the (1) total financial cost which includes the traditional per piece costs of tooling, consumables, acquisition, and direct labor, plus the financial costs associated with utilities purchase and by-products disposition (e.g., landfill tipping fees and selling recyclable materials), (2) an environmental *SPS* in millipoints which is made up of the environmental impacts due to energy use, resources use, and by-products release, and (3) the inventory of environmental burdens associated with the manufacturing process.

3.4.1. Boundaries of Process Accounting

Production lines are 'built up' by assembling the required primary and auxiliary production equipment in the front end, and the aggregate line performances estimated by summing individual machine performances in the back end. Not explicitly included in performance estimates here:

- All forms of indirect labor (e.g., line engineers, supervisors, material handlers, technicians, etc.);
- Quality costs (e.g., labor to conduct inspections: incoming materials, in-process, and finished parts; scrapped parts, etc.)
- Overhead costs;
- Facility operating costs (e.g., utilities, maintenance, permits, taxes, rent, etc.);
- Environmental and cost concerns related to production machinery and the manufacturing facility in life cycle phases other than use (i.e., materials acquisition, construction and assembly, and end of life dispositions);
- Environmental and cost concerns of the part in life cycle phases other than manufacture (i.e., materials acquisition, distribution, use, and end of life disposition); Of particular note, the cost of the workpiece material is *not* included, but manual inclusion of the standard cost of the pre-production part is simply done.
- Costs and environmental impacts outside the walls of the manufacturing facility proper (e.g., municipal waste water treatment, employee commuting, logistics and transportation systems, etc.).

Other tools, methods, and models are needed to address the above items, which may or may not be easily accomplished, but knowledge of these items is necessary support for other life cycle decision making activities.

3.4.2 Mathematical Modeling of Manufacturing Performances

In this section detailed explanation of the mathematical models used to estimate manufacturing environmental and cost performances are given. Primary and auxiliary machinery are presented separate from each other because of the different way in which they interact with the unit of production, which causes per piece environmental burdens to be attributed differently. The cost performance of a manufacturing process is defined here as the traditional machine costs of acquisition and tooling, plus the costs of utilities and consumables purchases and use (e.g., electricity, gases, fluids, filters, etc.), and by-products disposition (e.g., landfill tipping fees, special waste handling costs, income from the sale of recyclable materials, emissions permitting, etc.). Environmental performance of a manufacturing process is defined here by the amounts of environmental burdens or loads generated by the operation of the production line; from the inventory of environmental burdens, itself a disaggregated measure of the environmental performance of the manufacturing process, an environmental impact single point score (SPS) may be computed by summing the environmental impact of the environmental burdens in the inventory, determined using an Eco-indicator 99 value. Considering the environmental performance of a manufacturing process requires a broader view of manufacturing than typically taken; consideration in the process flow is given not only to the WIP and finished parts, but also to the material and energy flows into and out of each processing step in the production line. These flows, considered by this method, are depicted in Figure 21 below; the mathematical models in the following sections are concerned with quantifying the amount of the items into and out of individual processing steps, from 1 to N, and then summing them to get overall, aggregate performance measures of proposed manufacturing processes for achieving specific part designs.

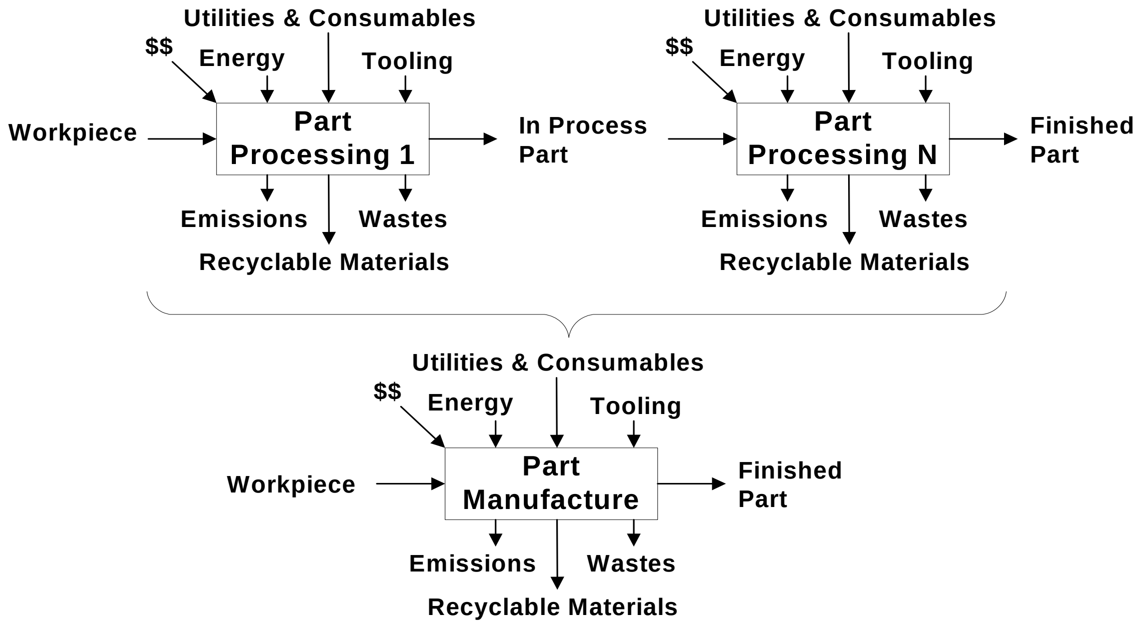

Figure 21 Flows in a Part's Manufacture

3.4.2.1 Estimating Environmental Burdens for Primary Machines

Primary machinery is that which operates directly on the parts being produced; examples are milling machines and part washers. Environmental burdens of primary machinery are attributed on a per unit of production basis using a generalized equation from which specific environmental burden estimates may be derived. Equation 1 is presented below and R_{SS} is steady state rate, and the time conversion is used as needed.

Environmental Burden of a Primary Machine (amount / part)

$$EB_{\text{primary}} = \left(R_{SS} \times T_{\text{proc}}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \text{time conversion} \tag{1}$$

The derivation of Equation 1 is accomplished by looking at the units of measure of the relevant machine parameters of interest; the parameters in Equation 1, with their units are listed below in Table 1. Desiring the variable EB_{primary} to have the units of amount per part (amount / part), it may be shown that the parameters of Table 1 must be arranged as in Equation 1.

Table 1 Input Parameter Units

Parameter	General Units	Example Units
R_{ss}	amount / time	lb / hr, kW
T_{proc}	time / process	hr, min
$N_{machines}$	no. machines	
S_{batch}	no. parts / process	

Substituting units in the place of parameters in Equation 1 yields the following:

$$\left(\frac{\text{amount}}{\text{time}} \times \frac{\text{time}}{\text{process}}\right) \times \frac{\text{no. machines}}{\text{no. parts}/\text{process}} = \frac{\text{amount}}{\text{part}} \times \text{no. machines}$$

Thus, the environmental burdens of a primary machine (EB_{primary}) may be estimated using Equation 1 and have the units of amount per unit of production, multiplied by the number of that particular primary machine. Processing or machining time is typically used for attributing environmental burdens to units of production because it is also commonly used in quoting for machine shop jobs and for attributing costs of production to units of production.

Examples of models used to calculate environmental burdens of a primary machine are given in Equations 2 – 5 below. When the environmental burdens for each primary machine in the process have been calculated, they may be summed to give the total environmental burdens of the proposed primary process.

Electrical Energy (kWh / part)

$$E_{\text{electrical}} = \left(P_{\text{electrical}} \times T_{\text{proc}}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \frac{1}{60} \tag{2}$$

Compressed Air (cf / part)

$$CA = \left(R_{\text{flow}} \times T_{\text{proc}}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \tag{3}$$

Water Use (gal / part)

$$W = \left(R_{\text{flow}} \times T_{\text{proc}}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \frac{1}{60} \tag{4}$$

By-products (lb / part)

$$BP = \left(R_{\text{gen}} \times T_{\text{proc}}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \frac{1}{60} \tag{5}$$

R_{flow} is in cfm and gph for Equations 3 and 4, respectively. Equation 5 is applicable for any by-product that may be generated by a process: landfillable materials, special or hazardous wastes, and recyclable materials, among others. The 60^{-1} factor in the above equations is simply the unit conversion between minutes and hours.

3.4.2.2 <u>Number and Sharing of Primary Machines</u>

The number of primary machines on a production line may be a non-integer value, due to sharing of machines with other production lines. When machinery is not shared between production lines the number of machines is simply an integer value. Input from process planners and manufacturing engineers should be sought in determining the correct number of machines required for the proposed process, unless the product designer is knowledgeable of this specific information. This information may be considered as ‘advanced’ knowledge of a process design, and is not likely to be known until both the product and process design are well defined, or the production process already exists. For the situation where primary machinery is shared between production lines, two methods for determining the number primary machines attributable to the production line of interest, for different starting assumptions, are given.

Assuming Equal Sharing

For approximately equal use between production lines, the machine fraction (or number) to attribute performances to the production line of interest is computed using Equation 6.

$$f = \frac{\text{No. primary machines}}{\text{No. production lines using machine}} \tag{6}$$

For example, a heat treat furnace may be used to heat treat parts from a number of production lines. Say there are two heat treat furnaces that are used by ten production lines. Assuming relatively equivalent production rates by those ten lines, the fraction of the heat treat furnaces used by one production line for a part of interest would be 0.20. Each production line is assumed to be using the heat treat furnaces equally.

Assuming Unequal Sharing

For production lines with disparate production rates, the machine fraction is determined by the relative use of the machine by the production line of interest, using Equation 7.

$$f = \text{No. primary machines} \times \frac{\text{Production rate for line of interest}}{\text{Total production rate of lines sharing machine}} \tag{7}$$

For example, say that the two heat treat furnaces are now used by only two production lines, A and B. The production rate of line A is twice that of B, thus the fraction of the heat treat furnace attributed to process A would be 1.333, since production line A uses two-thirds of the two heat treat furnaces. It may be shown using Equation 7 that,

$$f_A = 2 * (2 / 3) = 1.333$$

This second formula is a generalization of the special case where the use between production lines is equal; that is, the production rates are the same. Equation 7 may also be used in that special situation to determine the machine fraction (or number) for the production line of interest.

A Double Check

A quick check for both formulas is that the sum of the fractions for machine use for the individual production lines will sum to the total number of primary machines.

For example, for the 2 heat treat furnaces of the last example, f_A was found to be 1.333, and f_B may be shown to be 0.667 ($f_B = 2 * (1 / 3) = 0.667$).

$$f_A + f_B = 1.333 + 0.667 = 2$$

3.4.2.3 <u>Estimating Environmental Burdens for Auxiliary Machines</u>

Auxiliary machinery is that which supports the main processing steps of part's manufacture but is not directly involved in creating the part itself. Examples of auxiliary machinery, also sometimes called complementary (Graedel 1998), are coolant systems, dust collectors, mist collectors, and material handling equipment. Auxiliary machinery may support more than one production line simultaneously. For example, a coolant system may circulate and filter the cutting fluid used in a grinding operation used on multiple production lines turning out different parts. This sharing by multiple lines will decrease the per piece cost and environmental burdens and impacts of the auxiliary machinery. Environmental burdens of auxiliary machinery are attributed on a per unit of production basis using a generalized equation from which specific environmental burden estimates may be derived. Equation 8 is presented below and R_{SS} is steady state rate, the time conversion is used as needed, and the hourly production rate (*HPR*) for auxiliary machinery is the summed *HPR* for all production lines it supports, which may be only one.

Environmental Burden of an Auxiliary Machine (amount / part)

$$EB_{aux} = \left(\frac{R_{SS}}{HPR}\right) \times N_{\text{machines}} \times \text{time conversion} \tag{8}$$

The derivation of Equation 8 is accomplished by looking at the units of measure of the relevant machine parameters of interest; the parameters in Equation 8, with their units are listed below in Table 2. Desiring the variable EB_{aux} to have the units of amount per part (amount / part), it may be shown that the parameters of Table 2 must be arranged as in Equation 8.

Table 2 Input Parameter Units

Parameter	General Units	Example Units
R_{SS}	amount / time	lb / hr, kW
HPR	no. parts / time	1 / hr
N_{machines}	no. machines	

Substituting units in the place of parameters in Equation 8 yields the following:

$$\left(\frac{\text{amount}/\text{time}}{\text{no. parts}/\text{time}}\right) \times \text{no. machines} = \frac{\text{amount}}{\text{part}} \times \text{no. machines}$$

Thus, the environmental burdens of an auxiliary machine (EB_{aux}) may be estimated using Equation 8 and have the units of amount per unit of production, multiplied by the number of that particular auxiliary machine. Because auxiliary machinery does not directly interact with production parts, the parameter of processing time is not used to attribute auxiliary machine environmental burdens to production parts. In this method, the hourly production rate of the primary machines supported by an auxiliary machine is the chief parameter in attributing auxiliary machine environmental performance to units of production. The determination of hourly production rate is discussed in a later section in this chapter.

Examples of models used to calculate the environmental burdens of an auxiliary machine are given in Equations 9 - 12 below. When the environmental burdens for each auxiliary machine in the process have been calculated, they may be summed to give the total environmental burdens of the proposed auxiliary process.

Electrical Energy (kWh / part)

$$E_{\mathrm{electrical}} = \left(\frac{P_{\mathrm{electrical}}}{HPR} \right) \times N_{\mathrm{machines}} \qquad (9)$$

Compressed Air (cf / part)

$$CA = \left[\frac{R_{\mathrm{flow}}}{HPR} \times N_{\mathrm{machines}} \right] \times \frac{1}{60} \qquad (10)$$

Water Use (gal / part)

$$W = \left(\frac{R_{\text{flow}}}{HPR} \right) \times N_{\text{machines}} \tag{11}$$

By-products (lb / part)

$$BP = \left(\frac{R_{\text{gen}}}{HPR} \right) \times N_{\text{machines}} \tag{12}$$

In the context of auxiliary machinery, hourly production rate (*HPR*) is equivalent to the sum of the hourly production rate of the N production lines they support. R_{flow} is in cfm and gph for Equations 10 and 11 respectively. Equation 12 is applicable for any by-product that may be generated by a process: landfillable materials, special or hazardous wastes, and recyclable materials, among others. Again, the 60^{-1} factor is simply a unit conversion between minutes and hours.

After the environmental burdens for the primary and auxiliary machines in the manufacturing process are estimated, they may be summed to determine the process inventory. Environmental burdens associated with primary and auxiliary machines, such as energy and landfill wastes, may then be further summed to find the total environmental burdens of a manufacturing process using Equation 13.

$$EB_{total} = EB_{primary} + EB_{aux} \tag{13}$$

3.4.2.4 Number and Sharing of Auxiliary Machines

The number of auxiliary machines on a production line may be a non-integer value, due to sharing with other production lines to support primary processes. When auxiliary machinery is not shared between production lines the number of machines is an integer value. Input from process planners and manufacturing engineers should be sought in determining the correct number of machines required for the proposed process, unless the product designer is knowledgeable of this specific information. This information may be considered as 'advanced' knowledge of a process design, and is not likely to be known until both the product and process design are well defined, or the production process already exists. For the situation where auxiliary machinery is shared between production lines, two methods for determining the number auxiliary machines attributable to the production line of interest, for different starting assumptions, are given.

Assuming Equal Sharing

The machine fraction (or number) to attribute performances to the production line of interest may be computed using Equation 14 when the assumption that the production lines supported all have roughly equal use of the auxiliary equipment has been made.

$$f = \text{No. auxiliary machines} \times \frac{\text{No. primary machines supported on production line of interest}}{\text{Total no. primary machines supported}} \qquad (14)$$

For example, a dust collector may be used to collect the metal dust from dry cutting operations on a number of production lines. Say there are two dust collectors that support twenty machines on ten production lines. The production line of interest has three dry cutting machines that are supported by the dust collectors. The fraction of the dust collectors used by the production line for the part of interest would be 0.30. Using Equation 14 the calculation is simply the following:

$$f = 2 * (3 / 20) = 6 / 20 = 0.30$$

Assuming Unequal Sharing

For production lines with disparate production rates, the machine fraction is determined by the relative use of the machine by the production line of interest, using the method shown in Equation 15.

$$f = N_{\text{aux}} \times \frac{\text{Transformed } N_{\text{primary}}}{\text{Transformed } N_{\text{primary, total}}} \tag{15}$$

Where N_{aux} is the number of auxiliary machines, and Transformed $N_{primary}$ is the transformed number of primary machines supported on the production line of interest, found using Equation 16.

$$\text{Transformed } N_{\text{primary}} = N_{\text{primary}} \times \frac{\text{Line of interest production rate}}{\text{Total production rate of lines sharing auxiliary machine}} \tag{16}$$

Where $N_{primary}$ is the number of primary machines supported on the production line of interest, and Transformed $N_{primary, total}$ is the transformed total number of primary machines supported, found using Equation 17.

$$\text{Transformed } N_{\text{primary, total}} = \sum \text{ Transformed} N_{\text{primary}} \tag{17}$$

For example, say that four dust collectors are used by three production lines, A, B, and C. There are fifteen total primary machines supported by the dust collectors and line A has six of them, B has four, and C has five. The production rate of line A is twice that of B, and B and C have equivalent production rates. Thus the fraction of the dust collectors attributed to process A would be calculated using the method of Equations 15, 16, and 17.

A_{trans} = No. primary machine supported on line A * (line A production rate / total production rate of lines sharing dust collectors) = 6 * (2/4) = 3

B_{trans} = No. primary machine supported on line B * (line B production rate / total production rate of lines sharing dust collectors) = 4 * (1/4) = 1

C_{trans} = No. primary machine supported on line C * (line C production rate / total production rate of lines sharing dust collectors) = 5 * (1/4) = 1.25

T_{trans} = Total transformed = A_{trans} + B_{trans} + C_{trans} = 3 + 1 + 1.25 = 5.25

f_A = No. aux machines * (A_{trans} / T_{trans}) = 4 * (3 / 5.25) = 2.29

The fraction / number of the dust collectors attributable to production line A is shown to be 2.29.

This second method is a generalization of the special case where the use between production lines is equal; that is, the production rates are the same. Equations 15, 16, and 17 may also be used in that special situation to determine the machine fraction (or number) for the production line of interest.

A Double Check

A quick check is that the sum of the fractions for machine use for the individual production lines will sum to the total number of auxiliary machines.

For example, for the four dust collectors of the previous example, f_A was found to be 2.29, f_B may be shown to be 0.76 ($f_B = 4 * (1 / 5.25) = 0.76$), and f_C may be shown to be 0.95 ($f_C = 4 * (1.25 / 5.25) = 0.95$), which sum to 4 by:

$$f_A + f_B + f_C = 2.29 + 0.76 + 0.95 = 4$$

3.4.2.5 Auxiliary Hourly Production Rate

Because auxiliary machines do not directly affect or create the production of parts, but rather support the primary machines that directly create production parts, the parameter ‘processing time’ may not be used in attributing performances. The parameter used to attribute items for auxiliary machines to units of production is the hourly production rate of each primary machine supported by that auxiliary machinery. Two methods for determining the auxiliary hourly production rate, for different starting assumptions, are given in the following.

Assuming Equal Sharing and Support

If the assumption is made that all production lines supported by the auxiliary machinery have the same production rates *and* the same number of machines supported on each production line, the auxiliary 'hourly production rate' is simply:

HPR_{aux} = No. lines supported * No. machines supported per line * hourly production rate per primary machines supported

Where the hourly production rate per primary machine supported is assumed to be equivalent to the overall production line hourly production rate. In other words, each machine in a production line finishes parts at approximately the same rate as the entire production line. This assumption means that line flow and balancing dynamics internal to the production line (e.g., batching due to primary machinery with very different processing rates) is not taken into account.

For example, if an auxiliary machine supports three primary machines each on five production lines that are each producing parts at a rate of one hundred per hour, the auxiliary hourly production rate can be found to be 1500 parts / hr by:

HPR_{aux} = 5 lines * 3 machines / line * 100 parts / hr = 1500 parts / hr

Again, the assumption made here is that each primary machine on each production line is sharing the auxiliary equipment equally.

A simpler example to further demonstrate the calculation: an auxiliary machine is used to support two primary machines on one production line turning out parts at two hundred fifty per hour. The auxiliary hourly production rate may be found to be 500 parts / hr by:

$$HPR_{\mathrm{aux}} = 1 \text{ line} * 2 \text{ machines / line} * 250 \text{ parts / hr} = 500 \text{ parts / hr}$$

Assuming Unequal Sharing and / or Support

More generally, for production lines with rates that are not equal and / or disparate numbers of primary machines are supported from line to line, for an auxiliary machine that supports N production lines, the auxiliary hourly production rate may be found using Equation 18.

$$HPR_{aux} = \sum_{i=1}^{N} HPR_i \qquad (18)$$

Where HPR_i is the summed hourly production rate of all primary machines supported on the i^{th} production line. In other words, for M_i primary machines supported on the i^{th} production line HPR_i is found using Equation 19.

$$HPR_i = \sum_{j=1}^{M_i} HPR_j \qquad (19)$$

Rewriting, HPR_{aux} may be found using Equation 20. The units for HPR_j are parts per machine-hour.

$$HPR_{aux} = \sum_{i=1}^{N} \sum_{j=1}^{M_i} HPR_j \tag{20}$$

For example, say one mist collector supports primary machines on two production lines, A and B. The three primary machines on line A have production rates of 400, 250, and 150 parts per machine-hour, respectively. WIP parts are housed in 'markets' on the line. The two primary machines on line B both have a production rate of 200 parts per machine-hour. The hourly production rate of the auxiliary mist collector, used to attribute its performance to units of production, is calculated using Equations 18, 19, and 20, and may be shown to be 1200 parts / hour by:

$$HPR_A = \sum_{j=1}^{3} HPR_j = 400 + 250 + 150 = 800$$

$$HPR_B = \sum_{j=1}^{2} HPR_j = 200 + 200 = 400$$

$$HPR_{aux} = \sum_{i=1}^{2} HPR_i = HPR_A + HPR_B = 800 + 400 = 1200$$

This formula may be used as well under the first assumption that the production rates are all equal and each production line has the same number of primary machines supported by the auxiliary machine.

3.4.2.6 Energy and Emissions

Energy is an important environmental burden due to the increasing costs of energy and the nonrenewable nature of most energy sources. Energy in a manufacturing facility typically comes in the form of electricity, compressed air, natural and other gases, and steam. Compressed air, natural gas, and steam usage though typically do not have their units given in terms of energy, rather are they are expressed in units of cf and lbs commonly. They may be converted using the conversion factors 0.293 kWh / cf and 0.293 kWh / lb, respectively (PNNL 2003, AGA 2004). The non-converted units are used in the calculations for environmental impact and financial costs however.

The conversion factor for another common energy source, compressed air, is not as accepted or well known. However, a reference has been found stating that 0.21 kWh is required to compress 1 cf of compressed air (Talbert 2006). Assuming no losses and 100% efficiency, the energy potential of compressed air may be thought to be equivalent to the electrical energy required to run the motor to compress it. Thus the conversion factor for compressed air energy could be 0.21 kWh / cf, which is used in the examples of this thesis. For a particular manufacturer, the conversion factor relating compressed air to energy needs determination depending on the specifics of their compressed air system.

Carbon dioxide emissions are another very important environmental burden as CO_2 related to industrial activity is linked to potential climate change. CO_2 is produced directly through the burning of fossil fuels in operations such as heat treatment. Electricity production, when done by burning fossil fuels, releases CO_2 that is indirectly attributed to the plant by its electricity usage. CO_2 emissions may be found with the conversion factors 0.668 tons CO_2 / MWh of electricity and 5.85×10^{-5} tons CO_2 / cf of natural gas[1] (EIA 1998, EIA 2002). If other emissions are of concern (e.g., NO_x, SO_2, etc.) either as direct or indirect releases, these could be included as well. The US EPA is an excellent resource for emissions data and conversion factors (coefficients) (EIA 2002).

3.4.2.7 Traditional Machine Costs and Direct Labor Cost

The per unit of production traditional financial costs of tooling, consumables, and acquisition are calculated the same way for both primary and auxiliary machinery using traditional cost accounting. The key difference being that hourly production rate (*HPR*) for primary machinery is the *HPR* for that one part's production line, while *HPR* for auxiliary machinery is the summed *HPR* for all machinery on the production lines it supports, which may only be one. Additionally, since auxiliary equipment does not work directly on the unit of production, there is no production tooling and thus the tooling cost category is not included for auxiliary machines. Traditional cost accounting is used due to its simplicity in use, though it may be less accurate than activity based costing. For per piece financial costs, models are of the form (Total Yearly Cost / Hours/year) / Hourly Production Rate; where total yearly cost is the number of machines multiplied by the yearly cost per machine. The traditional costs of machinery are modeled per unit of production in Equations 21 – 23.

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[1] According to the US Department of Energy, 117,000 pounds of CO_2 is released per billion Btu of heat energy extracted from natural gas (EIA 1998).

Per Piece Tooling ($ / part)

$$C_{\text{tool, pp}} = \left(\frac{C_{\text{tool}} \times N_{\text{machines}}}{HPY} \right) \times \frac{1}{HPR} \tag{21}$$

Per Piece Consumables ($ / part)

$$C_{\text{Q, pp}} = \left(\frac{C_{\text{Q}} \times N_{\text{machines}}}{HPY} \right) \times \frac{1}{HPR} \tag{22}$$

Per Piece Acquisition ($ / part)

$$C_{\text{acq, pp}} = \left(\frac{C_{\text{acq}} \times N_{\text{machines}}}{HPY \times T_{\text{depreciate}}} \right) \times \frac{1}{HPR} \tag{23}$$

The per piece acquisition cost requires an extra term in its calculation, the number of years to depreciate machinery. After the years to depreciate capital costs have passed, per unit of production machine acquisition costs may be dropped from the financial costs calculations. It is ideal that production machinery be used as long as possible so as to increase its value to a manufacturer. Also, if older machines are to be used in the proposed process, the level of depreciation / amortization needs to be considered as it impacts the amount of acquisition costs to be attributed to units of production.

Shehab and Abdalla (Shehab, et al. 2001) propose that the same machine costs estimated using Equations 21, 22, and 23, be determined using a machine cost rate (C_{M} with units of $ / time), shown in Equation 24, multiplied by the machining (processing) time. The methods of Equations 21, 22, and 23 differ from that of Equation 24 by (1) using the inverse of hourly production rate (which is time per part) instead of machining time; for highly efficient processes, HPR^{-1} and machining time will be approximately equal, and (2) not including overhead because the items typically included in overhead (utilities, consumables, etc.) are more explicitly considered in their own price categories.

$$C_{\mathrm{M}} = \left[\frac{\text{Machine Cost}}{\text{Working Hours Per Year}}\right] \times (1 + \text{Overhead}) \tag{24}$$

Direct labor is the only type of labor considered in this method; indirect labor such as line engineers, material handlers, technicians, etc. is not considered. Additionally direct labor is assumed to be used only on the operation of the primary machines in the process; any 'direct' labor required for the operation of auxiliary equipment is not considered. The direct labor cost per unit of production is found using either of the following methods, shown in Equations 25 and 26, which yield identical results.

$$C_{\text{labor,pp}} = \frac{\text{direct labor cost per year}}{\text{yearly production}} \tag{25}$$

The labor cost per year is calculated by multiplying the labor hours per year by the operator labor rate. Labor hours per year is calculated by multiplying the number of operators on the production line by the hours of operation in a year. This method of calculating direct labor cost may be too abstract, so the alternative is also presented as Equation 26.

$$C_{\text{labor,pp}} = \frac{(\text{no. operators} \times \text{labor rate})}{HPR} \tag{26}$$

The hourly production rate is found by dividing the annual production rate by the hours per year. The hours per year is found by multiplying the hours per day by days per week by weeks per year.

Modeled in these ways, for parts to be produced under identical facility conditions (i.e., number of shifts per day or week, annual production volume, number of weeks per year, etc.) the only factor that will differentiate the direct labor cost between different part designs is the number of operators required to man the proposed production lines.

Shehab and Abdalla (Shehab, et al. 2001) propose calculating labor per part using a labor cost rate found using Equation 27, which is similar to the rate contained in Equation 24 . The labor cost rate (C_L with units of $ / time) is again multiplied by machining (processing) time to determine the labor cost of producing a part, the same as the cost determined using either Equation 25 or 26. The difference between these methods is the use of hourly production rate or yearly production, in the place of machining (processing time) as the time factor of the labor rate, and the exclusion of overhead for the same reason discussed previously.

$$C_{\text{L}} = \frac{\text{Annual Labor Cost Including Overhead}}{\text{Working Hours Per Year}} \tag{27}$$

Combining the utilities and by-products costs, calculated in an activity based fashion by converting the items from the environmental burden inventory using cost rates, with these more traditional per piece costs shown above yields the total financial cost. Determining the financial costs of utilities and by-products is discussed in the next section.

3.4.2.8 Environmental Impact Score and Other Financial Costs

Environmental impacts and the single point environmental score are calculated simply enough; the amount of environmental burden estimated previously and stored in the inventory is multiplied by its Eco-Indicator 99 value stored in a database. Performing this operation on all items in the inventory and summing them yields the *SPS*. For environmental impacts, models are of the form: (amount in inventory * eco-indicator value)* unit conversion factor (if needed).

Costs for utilities and by-products are computed similarly; the amount in the inventory is multiplied by the cost rate also stored in a database. Combining the utilities and by-products costs with the other, more traditional, per piece costs shown above yields the total financial cost. For financial costs of utilities and by-products, models are of the form: (amount in inventory * cost rate)*unit conversion factor (if needed).

For example, consider a hypothetical process which requires 0.10 kWh of electricity per unit of production. Using the eco-indicator value of 25.67 mpt / kWh from Sima-Pro LCA software for the US electricity grid, and the cost rate of $0.04 / kWh, the environmental impact and financial cost of the 0.10 kWh of electricity are calculated as follows:

0.10 kWh / part * 25.67 mpt / kWh = 2.567 mpt / part

0.10 kWh / part * $0.04 / kWh = $0.004 / part

The summations for environmental impacts, with units of mpt / part, and financial costs, with units of \$ / part, to determine the totals of those items are given in Equations 28 and 29, respectively.

$$SPS = \sum_{j=1}^{m} EI_j \tag{28}$$

$$C_{total} = C_{labor} + C_{tool} + C_{acq} + C_Q + \sum_{k=1}^{m_1} C_{utilities,k} + \sum_{l=1}^{m_2} C_{by-products,l} \tag{29}$$

In Equation 28 EI_j is the environmental impact of the jth utility, resource, or by-products of m total items, associated with the manufacturing process. In Equation 29, m_1 and m_2 sum to equal m, the total number of utility and by-product items.

3.4.3 Parametric Studies of Manufacturing Performance Models

Product tolerances strongly influence manufacturing operations through process and machine selection, and also machine operation. Selection of machines is addressed in the method with the filtering operation of the front end process generation; however, that does not give the full picture of the relationship between product tolerancing decisions and manufacturing performance. Abstracting out the specific machine operating parameters (e.g., MRR, number of cutting passes, etc.) tolerance requirements will influence total primary machine processing time; that is, processing time is a function of tolerance requirements. According to (DeGarmo, et al. 1997) processing time is calculated using the amount of material to be removed and the MRR or feed rate, a component of MRR calculation; processing time and feed rate are inversely related. For tighter part feature tolerances the feed rate, and thus the MRR, will decrease causing processing time to increase. The relationships between part feature tolerances and feed rate, processing time and feed rate, and processing time and part feature tolerance are given by Equations 30, 31, and 32, respectively.

$$\mathrm{f} \propto t \tag{30}$$

$$T_{\mathrm{proc}} \propto \frac{1}{\mathrm{f}} \tag{31}$$

$$T_{proc} \propto \frac{1}{t} \tag{32}$$

In Equation 30 it is seen that feed rate and part feature tolerance are directly related; as f increases *t* does likewise, and vice versa. In Equation 31 the inverse relationship between feed rate and processing time is given, and in Equation 32 part feature tolerance is substituted for feed rate using Equation 30. It is seen that as *t* increases, T_{proc} decreases; processing time and feature tolerance are inversely related.

Additionally, for a fixed number of primary machines, the hourly production rates supported by auxiliary machines are a function of primary machine processing times, which are themselves a function of part feature tolerances. Longer processing times resulting from tighter tolerance requirements will reduce the rate of production of which a primary machine is capable, and thus the hourly production rate supported by auxiliary machines supporting that primary machine will decrease as well. The relationship between the hourly production rate (*HPR*) supported by an auxiliary machine, primary processing time, and part feature tolerance is given by Equation 33.

$$HPR \propto \frac{1}{T_{proc}} \propto t \tag{33}$$

As t increases (i.e., tolerance becomes looser), so does *HPR*; feature tolerance and hourly production rate are directly related. As T_{proc} increases however, *HPR* decreases; processing time and hourly production rate are inversely related.

Assuming that detailed processing planning (e.g., depth of cuts, width of cuts, tool rpm, feed rates, etc.) has been done to optimally set machining parameters for the necessary cuts required by a machine, processing time may be considered as a proxy measure of the tolerance specified on a feature.

The 'knobs' to turn by the user of the method to update and adjust processing time for primary machines will be clearly identified, along with the hourly production rates supported for auxiliary machines, from the typical values contained in the database, thus improving the accuracy of performance estimates. A couple methods for determining these important items will later be discussed, but in the next sections those knobs will be turned in order to investigate machine operation (and thus performance) as a function of tolerance.

3.4.3.1 <u>Primary Machine Environmental Burdens</u>

In this section a simple parametric study of the environmental burden model for primary machines in order to show the generic manufacturing performance response (measured by quantity of environmental burdens) to changing tolerance levels within a selected machine's tolerance capability. The quantities of environmental burdens estimated form the basis for calculating the other important manufacturing performance indicators of environmental impact score and the financial costs of those burdens (e.g., utilities and by-products). Recalling Equation 1 above, repeated below, assuming machines are operating 'fully on' for all types of processing and thus constant environmental burden rate as a function of tolerance (which may or may not be an accurate assumption), environmental burdens of a primary machine may be shown in to be linearly related to processing time.

$$EB_{\text{primary}} = \left(R_{\text{SS}} \times T_{proc}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \text{time conversion} \tag{1}$$

Previously discussed, processing time is a function of the feature tolerance; a linear relationship will be assumed whereby 60s is the processing time required to achieve a machine's tolerance limit, and 10s is the processing time to achieve a much looser feature tolerance, say 0.050in., essentially putting an upper bound on tolerance. In the primary machine database there is only a specified a limit on tolerance (a lower bound) because a machine may create features as sloppily (with little precision) as possible, but there is a limit to achievable precision. However, an upper bound on feature tolerance is necessary for specifying a linear curve fit. The simplification of processing time as a linear function of part feature tolerance is primarily done because the exact relationship is not known. Generally, the coefficient of the relationship needs empirical determination via statistical regression methods and depends on the detailed machining process parameters set to achieve the required part feature tolerances.

Examples of relationships between processing time and feature tolerance, for non-traditional machining tolerances may be found in (Yeo, et al. 1997); the cost-tolerance relationships for electrical discharge wire machining (EDWM) and laser beam machining (LBM) were examined. In the study the machining times required for achieved feature tolerances were reported; these data points are plotted and linear curve fits applied for EDWM and LBM in Figures 22 and 23, respectively. The linear forms of the relationships are given on the plots, along with the R^2 value which is a measure the goodness or closeness of the model approximation to the actual data. In both Figures 22 and 23 machining time is seen to increase with decreasing feature tolerance. Also, the fairly high R^2 values of 0.87 and 0.90 (R^2 approaching 1.00 is desired) for the linear curve fits in Figures 22 and 23, respectively, indicate that the simple linear approximations sufficiently model the empirical data. The R^2 value may be improved with higher order approximations, but the tradeoff between accuracy gains and model simplicity (and cost) must be considered.

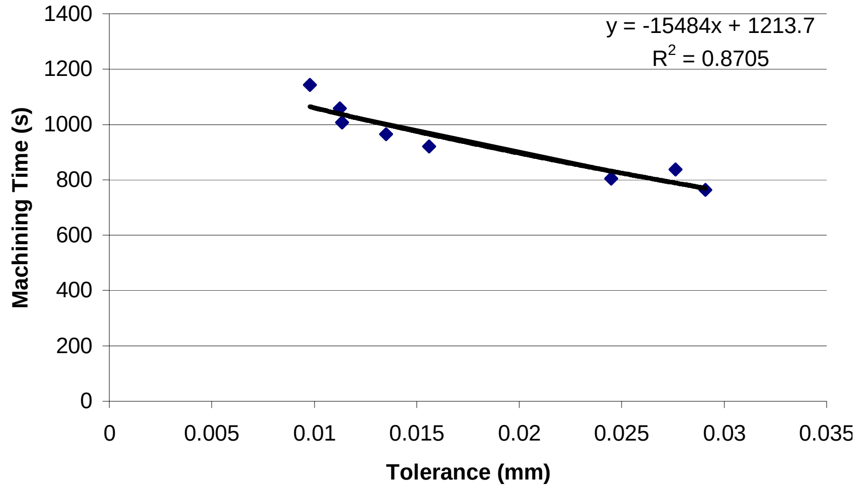


Figure 22 Machining Time as a Function of Tolerance in EDWM

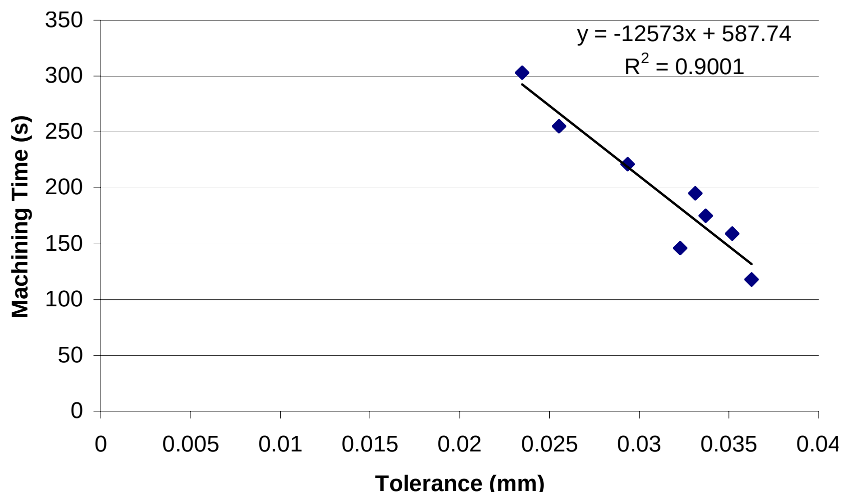


Figure 23 Machining Time as a Function of Tolerance in LBM

Though the relationships in Figures 22 and 23 are for non-traditional machining operations, they are presented as support for a linear processing time and part feature tolerance relationship. More accurate relationships could be used, but given the lack of information besides the processing times at the bounds of tolerance capability for the assumed situation, a linear approximation is simply good enough. When more information, or a better model, for processing time as a function of feature tolerance is known or available, it can and should be used in the place of this linear relationship. Non-linear relationships between processing time and part feature tolerance will be discussed later. The assumed linear relationship between the processing time and feature tolerance is given by Equation 34.

$$T_{proc} = -k_i t + c_i \tag{34}$$

Where in Equation 34, T_{proc} is processing time, k_i is an empirically determined coefficient relating feature i's tolerance to processing time, c_i is an empirically determined constant, and t is specified feature tolerance. For the assumed, known processing times at the tolerance capability limits of a primary machine, given in Table 3, the linear relationship of Equation 34 requires that k_i be -1020.4 and c_i be 61.02. This linear model is depicted in Figure 24, and will be used in connecting environmental burden estimates of both primary and auxiliary machines to part feature tolerances.

Table 3 Processing Times at Tolerance Capability Limits

Processing Time (s)	Tolerance (in.)	
10	0.050	Upper Tolerance Limit
60	0.001	Lower Tolerance Limit

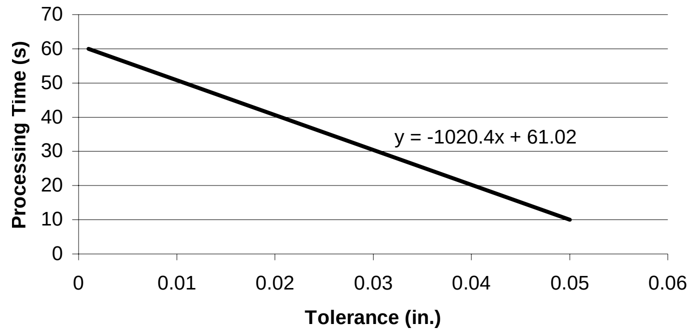


Figure 24 Processing Time as a Linear Function of Part Feature Tolerance

Recalling Equation 1, the environmental burdens of a primary machine are given by the following.

$$EB_{\text{primary}} = \left(R_{\text{SS}} \times T_{proc}\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \text{time conversion} \tag{1}$$

Looking at Equation 1 it is seen that for fixed environmental burden rate, number of machines, and batch size, the amount of environmental burden for a primary machine attributed to a unit of production is linearly and directly related to part processing time. This relationship is plotted in Figure 25.

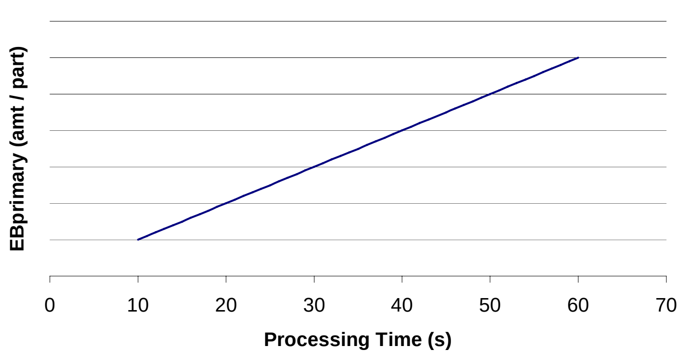


Figure 25 Primary Machine Environmental Burden as a Function of Processing Time

Thus, for fixed rate of the environmental burden, number of primary machines, and batch size, the amount of an environmental burden for a primary machine, as a function of feature tolerance is found by substituting the processing time – feature tolerance relationship of Equation 34 into Equation 1, shown below in Equation 35.

$$EB_{\text{primary}} = \left(R_{\text{SS}} \times \left(-k_i t + c_i\right)\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \text{time conversion} \tag{35}$$

Combining the all the fixed values in Equation 35 into collected constants the equation for environmental burdens of a primary machine as a function of feature tolerance is shown in Equation 35. This relationship is also plotted in Figure 26.

$$EB_{\text{primary}} = m(-k_i t + c_i) = -Ct + b \tag{36}$$

Where in Equation 36:

m=R_{SS}*N_{machines} / S_{batch} * time conversion

C=m* k_{i}

b=m*c_{i}

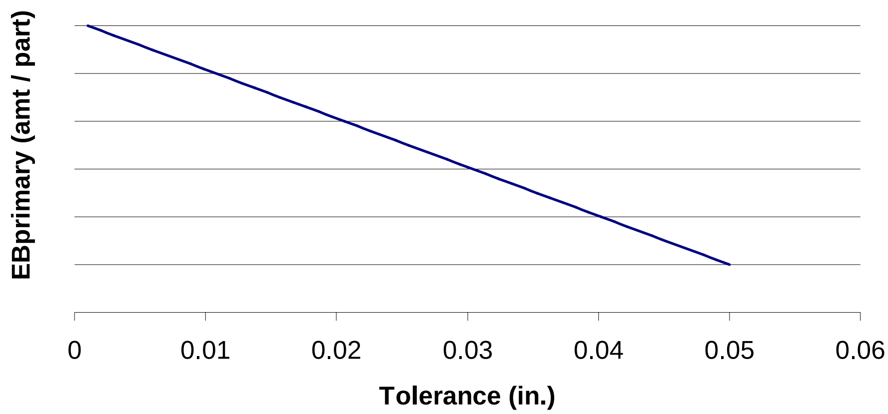


Figure 26 Primary Machine Environmental Burden as a Function of Part Feature Tolerance

As expected the relationship between environmental burdens generated by a primary machine is shown to be inversely and linear related to part feature tolerance specification. Because processing time increases with lower (i.e., tighter) tolerance levels, the amount of environmental burdens attributed to the unit of production under operation will likewise increase. The exact form of the primary machine environmental burdens as a function of feature tolerance is wholly dependent on the nature of the processing time – feature tolerance relationship. A simple linear relationship has been examined above; non-linear processing time – feature tolerance relationships will be discussed next.

Non-linear Processing Time – Feature Tolerance Relationships

The assumption of a linear processing time – feature tolerance relationship may be good enough in many instances; however the relationship between processing times required to achieve specified part feature tolerances is not necessarily this simple. Assuming the same processing times at the end points of a primary machine's tolerance capability, shown in Table 3 above, a non-linear processing time –feature tolerance relationship is selected to examine its effect on primary machine environmental burdens. A hypothetical exponential relationship is arbitrarily chosen with the required end points; it is plotted in Figure 27 with the model equation. This exponential model connecting part feature tolerance to processing time is also given in Equation 37.

$$T_{proc} = ce^{-dt} \tag{37}$$

In Equation 37 *c* and *d* are empirically determined constants. Using the hypothetical plot in Figure 27 *c* is set to be 62.235 and *d* 35.567.

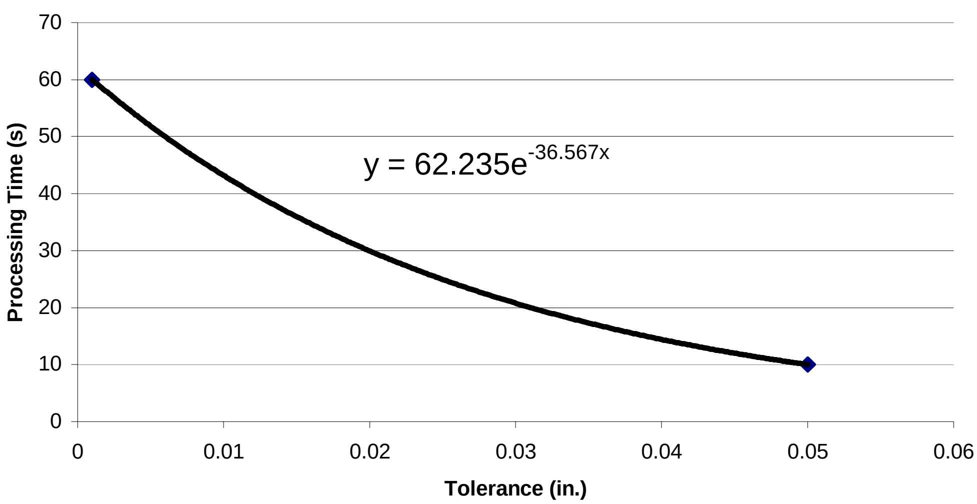


Figure 27 A Non-linear Relationship Between Processing Time and Feature Tolerance

Again recalling Equation 1, the environmental burdens of a primary machine, and going ahead and substituting Equation 37 into Equation 1, Equation 38 is given to relate feature tolerance to environmental burden.

$$EB_{\text{primary}} = \left(R_{\text{SS}} \times \left(ce^{-dt}\right)\right) \times \frac{N_{\text{machines}}}{S_{\text{batch}}} \times \text{time conversion} \tag{38}$$

Combining the all the fixed values in Equation 38 into collected constants the equation for environmental burdens of a primary machine as a function of feature tolerance is shown in Equation 39. This relationship is also plotted in Figure 28.

$$EB_{\text{primary}} = m(ce^{-dt}) = Ce^{-dt} \tag{39}$$

Where in Equation 39:

$m = R_{\text{SS}} * N_{\text{machines}} / S_{\text{batch}}$ * time conversion

$C = m * c$

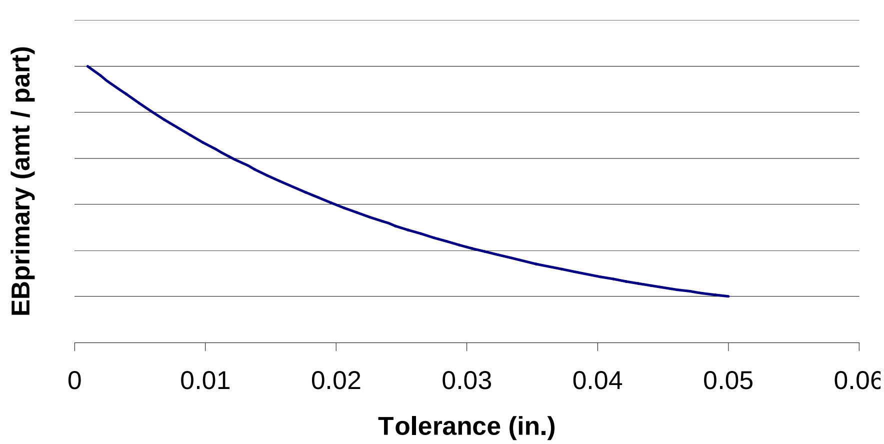


Figure 28 Primary Machine Environmental Burden as a Function of Part Feature Tolerance

The environmental burdens generated by a primary machine, and attributed to a unit of production, are again seen to be inversely related to part feature tolerance.

However, the relationship is no longer simple and linear as previously discussed and presented. This situation is due to the non-linear relationship between processing time and feature tolerance. This may be generalized to say that the exact form of the primary machine environmental burdens as a function of feature tolerance is wholly dependent on the form of the processing time – feature tolerance relationship. The model for processing time as a function of feature tolerance is substituted directly into the environmental burden model, and the shape of the environmental burden curve as a function of feature tolerance thus takes on that same shape as the processing time – feature tolerance curve. The coefficients and constants which will describe the environmental burden – feature tolerance curve are found using the environmental burden rates, number of machines, batch size, and the model for processing time as a function of feature tolerance.

The manufacturing performance of only one primary machine (as measured by environmental burden) has been considered to this point. In a high volume manufacturing environment, production rate levels are required from primary machines to achieve the planned production volumes, regardless of the necessary details and inner workings of the given operation to make quality parts to the specified part feature tolerance levels.

Considering Required Production Rate from a Primary Machine

Tightening features tolerances has been seen to increase the amount of processing time for a primary machine. In a production environment known quantities are required at a rate to meet the customer's scheduled demand for the parts being produced. When machine production rates drop below the required levels, additional primary production machinery is required to meet the needed rates. Adding machinery to a manufacturing process will most likely have cost and environmental implications that will likely degrade manufacturing performance. However, this reduction in manufacturing performance will occur when a level of production is to be held constant, regardless of the precision requirements of the parts to be produced.

In a later stage of product and process design, and certainly in manufacturing operations, the primary machine's cycle time, which includes non-processing times such as part wait and transfer times in addition to processing time, may be known and should be used to accurately estimate hourly production rate (*HPR).* In an early stage of product design however, cycle times of primary machines are not likely to be well known, and in fact are not necessarily a function of product design decisions, such as tolerance allocations. Cycle time includes the processing time, which is largely a function of the required feature tolerances, but the wait and transfer times are a function of individual primary machine workings, and dynamics and balance of the production line of which the primary machine is a part. Neglecting part wait and transfer times, the hourly production rate (*HPR*), perhaps more commonly known as jobs per hour (JPH) may be estimated using Equation 40, when T_{proc} is in seconds. For the assumed range of processing times between 10s and 60s, the reciprocal relationship between processing time and hourly production rate is also given in Figure 29.

$$HPR = \frac{3600}{T_{proc}} \qquad (40)$$

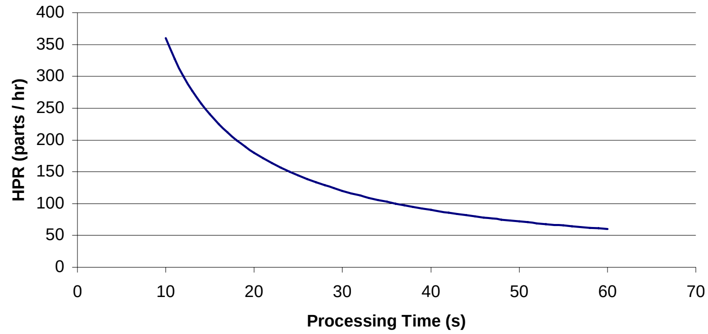


Figure 29 HPR as a Function of Processing Time

Say 180 production parts are required from a primary machine in an hour. Looking at Figure 29 it is clear that a single primary machine will not be able to make that production rate when processing times are above 20s, a common situation for tighter part feature tolerances. When the production rate drops below 180 parts per hour for a given tolerance specification, it becomes necessary to add primary machine(s). The number of primary machines as a function of *HPR* for the situation where 180 parts are required per hour from the operation conducted by a primary machine is depicted in Figure 30.

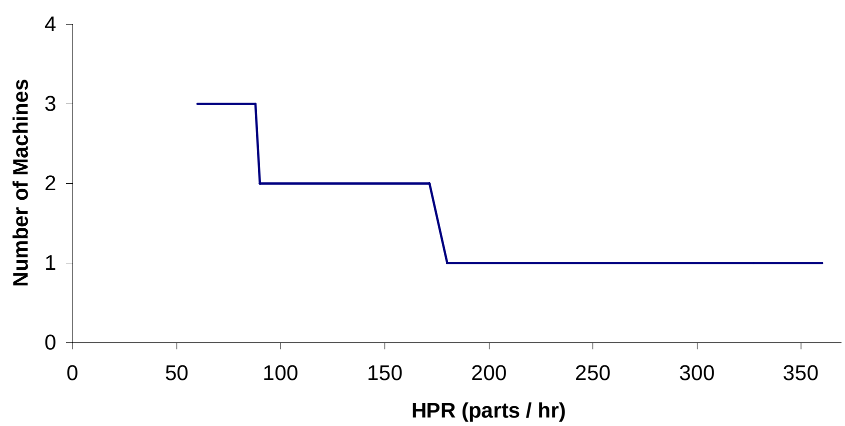


Figure 30 Number of Primary Machines vs. HPR Capability

For lower levels of *HPR*, more primary machines are needed to meet the required rate of 180 parts per hour. Recalling Equation 1, the environmental burdens of a primary machine, the number of machines multipliers the estimated environmental burden amount per machine to determine the total environmental burdens generated by a type of primary machine. Thus adding a primary machine, in addition to increasing initial acquisition costs, will increase the amount of environmental burdens. Using the knowledge of the assumed relationship between processing time and feature tolerance, processing time and HPR to determine the number of machines required, and environmental burdens as a function of processing time and number of machines, Figure 31, the primary machine environmental burdens as a function of feature tolerance, is given. Tightening tolerance levels will increase processing time, which will decrease HPR, and thus necessitate adding more primary machines to the production process.

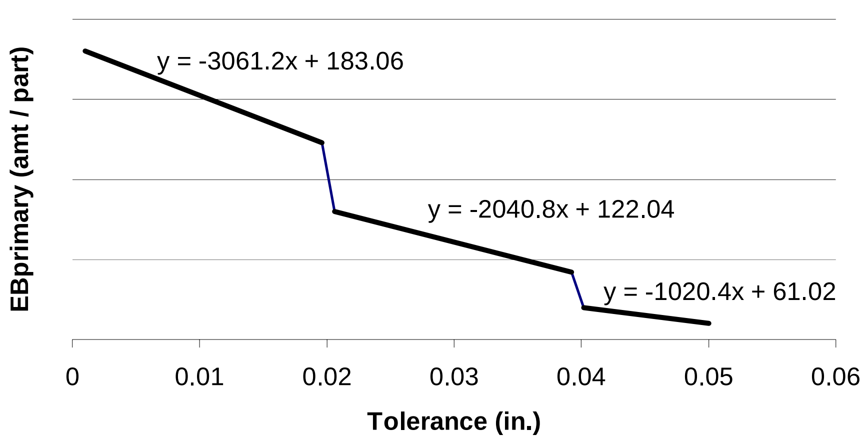


Figure 31 Primary Machine Environmental Burdens as a Function of Part Feature Tolerance, Considering Required Production Volumes

The shape of the curve in Figure 31 is not as simple as the one shown in Figure 26. The relationship is still linear, though there are now jumps, or discontinuities, at those tolerance levels which drive the addition of another primary machine. The specific coefficient and constant values of the linear models shown in Figure 31 are not important; however, it is noted that these values are multiples of each other related by the number of primary machines required to achieve production volumes for a given part feature tolerance. The addition of primary machines required to maintain production rates for tighter feature tolerance not only causes upwards jumps in the amount of environmental burdens, as seen in Figure 31, but also increases the slope of the curve, meaning that for similar feature tolerance tightening there will be a more elastic environmental burden response.

The behavior of the environmental burden model for primary machines, which attributes this indicator of manufacturing performance on a per unit of production basis, has been discussed. Attention will now be turned to the environmental burden model for auxiliary machines.

3.4.3.2 Auxiliary Machine Environmental Burdens

In this section a simple parametric study of the environmental burden models for auxiliary machines will be conducted to show the generic manufacturing performance response to changing primary production levels. With tightening part feature tolerance levels, processing times for primary machines will increase, and hourly production rates will decrease, for the same number of primary machines in the process. Again assuming that environmental burden rates are also constant for an auxiliary production machine, the environmental burdens of an auxiliary machine are solely a function of the hourly production rate supported by the auxiliary machine. This is given by Equation 8, presented previously but recalled here. This inverse, reciprocal relationship between environmental burdens of an auxiliary machine and the hourly production rate supported by that machine is also shown in Figure 32.

$$EB_{aux} = \left(\frac{R_{SS}}{HPR} \right) \times N_{\text{machines}} \times \text{time conversion} \tag{8}$$

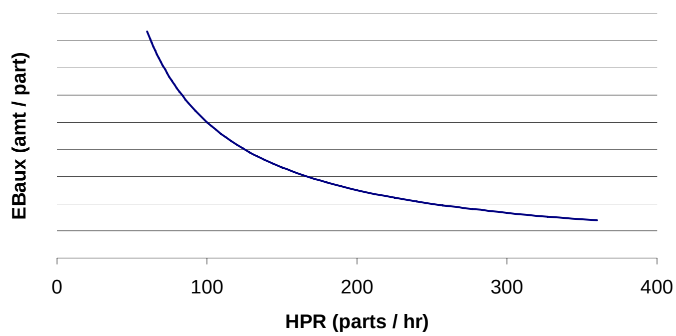


Figure 32 Auxiliary Environmental Burdens as a Function of HPR

Looking at Figure 32 it is seen that the environmental burdens generated by an auxiliary machine, and attributed to a unit of production, decrease as the production rate increases. Essentially manufacturing performance is improved by spreading the environmental loads, or costs, over a greater number of production pieces. For a given primary machine, as part feature tolerances become looser the hourly production rate supported by an auxiliary machine will increase, thus improving the auxiliary machine's cost and environmental performances.

Recalling Equation 40, and the plot in Figure 29, the auxiliary *HPR* supported for a primary machine with processing times of 10s and 60s at its upper and lower bounds of tolerance, respectively, is 360 and 60 parts per hour. For the loosest tolerance *HPR* is the highest (360), and for the tightest tolerance HPR is the lowest (60). Utilizing the linear relationship between feature tolerance and processing time, given in Equation 34 above, and substituting this linear relationship into the equation for *HPR* and processing time, given in Equation 40 above, a relationship between HPR and feature tolerance is given in Equation 41. This relationship is also plotted in Figure 33.

$$HPR = \frac{3600}{-k_i t + c_i} \qquad (41)$$

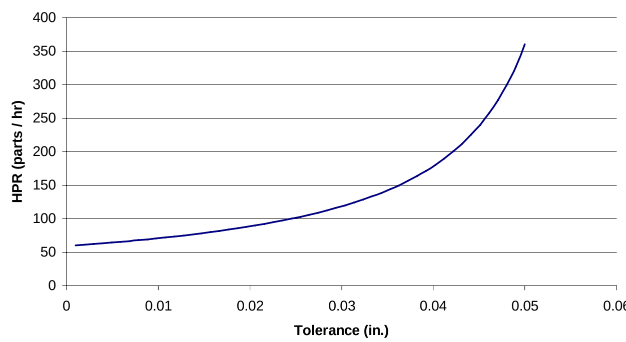


Figure 33 Auxiliary HPR Supported as a Function of Part Feature Tolerance

In Figure 33, the auxiliary HPR is seen to increase with loosening of feature tolerance, as expected. Substituting Equation 41 into Equation 8, the environmental burden for an auxiliary machine as a function of feature tolerance is shown in Equation 42.

$$EB_{aux} = \left(\frac{R_{SS}\left(-k_i t + c_i\right)}{3600} \right) \times N_{\text{machines}} \times \text{time conversion} \qquad (42)$$

Combining the all the fixed values in Equation 42 into collected constants the equation for environmental burdens of an auxiliary machine as a function of feature tolerance is shown in Equation 43, and has the identical form to the relationship between feature tolerance and the environmental burdens of primary machines. However, the calculation of the model constants is different. A plot of the relationship in Equation 43 is given in Figure 34.

$$EB_{aux} = m(-k_i T + c_i) = -CT + b \tag{43}$$

Where in Equation 43:

$m = R_{SS} * N_{machines} / 3600 * \text{time conversion}$

$C = m * k_i$

$b = m * c_i$

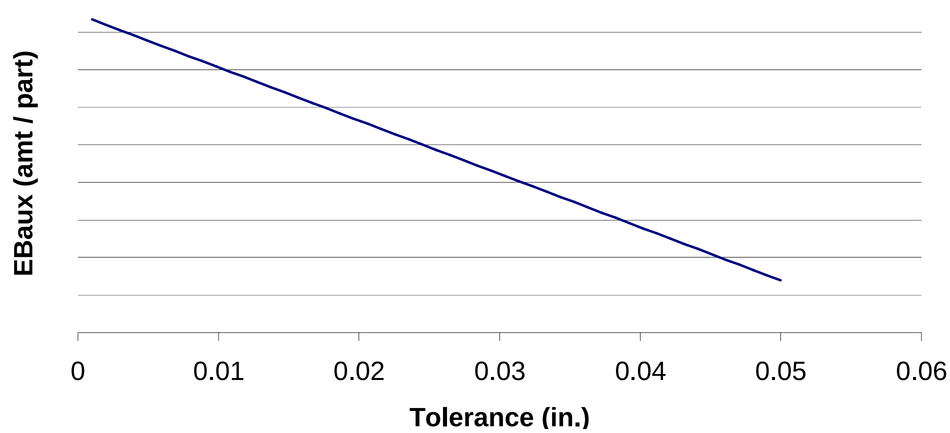


Figure 34 Auxiliary Machine Environmental Burden as a Function of Part Feature Tolerance

The environmental burdens generated by an auxiliary machine, and attributed to a unit of production, are again seen to be inversely, and linearly, related to part feature tolerance. The linear relationship is again based solely on the assumed linear relationship between part feature tolerance and primary machine processing time. Another non-linear processing time – feature tolerance relationship, and its effect on environmental burdens of an auxiliary machine, will be examined next. Before going there however, it is important to note that it is becoming overwhelmingly clear that looser part tolerances are favorable for both primary and auxiliary machines to improve the environmental performance in manufacturing. Improvements in cost performance are expected for a part with looser tolerances in its manufacture, per the literature and industrial experience, but the exact relationship has not been known or demonstrated previously.

Non-linear Processing Time – Feature Tolerance Relationships

The assumption of a linear processing time – feature tolerance relationship may be good enough in many instances; however the relationship between processing times required to achieve specified part feature tolerances is not necessarily this simple. Assuming the same processing times at the end points of a primary machine's tolerance capability, shown in Table 3 above, a different non-linear processing time –feature tolerance relationship is selected to examine its effect on auxiliary machine environmental burdens. A hypothetical logarithmic relationship is arbitrarily chosen with the required end points; it is plotted in Figure 35 with the model equation. This logarithmic model connecting part feature tolerance to processing time is also given in Equation 44.

$$T_{proc} = c\ln(t) + d \tag{44}$$

In Equation 44 *c* and *d* are empirically determined constants. Using the hypothetical plot in Figure 35 *c* is set to be -12.781 and *d* -28.289.

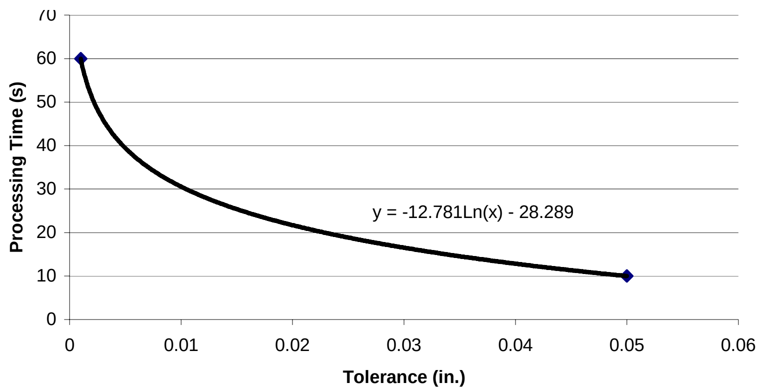


Figure 35 Another Non-linear Relationship Between Processing Time and Feature Tolerance

Recalling Equation 40, HPR as a function of feature tolerance may be found by substituting Equation 44; this is presented in Equation 45.

$$HPR = \frac{3600}{c\ln(t) + d} \tag{45}$$

Substituting Equation 45 into Equation 8, the environmental burdens of an auxiliary machine, Equation 46 is given to relate feature tolerance to environmental burden.

$$EB_{aux} = \left(\frac{R_{SS}\left(c\ln(t)+d\right)}{3600} \right) \times N_{\text{machines}} \times \text{time conversion} \tag{46}$$

Combining the all the fixed values in Equation 46 into collected constants the equation for environmental burdens of an auxiliary machine as a function of feature tolerance is shown in Equation 47. This relationship is also plotted in Figure 36.

$$EB_{aux} = m\left(c\ln(t)+d\right) = C\ln(t)+D \tag{47}$$

Where in Equation 47:

$m = R_{SS} * N_{\text{machines}} / 3600 * \text{time conversion}$

$C = m * c$

$D = m * d$

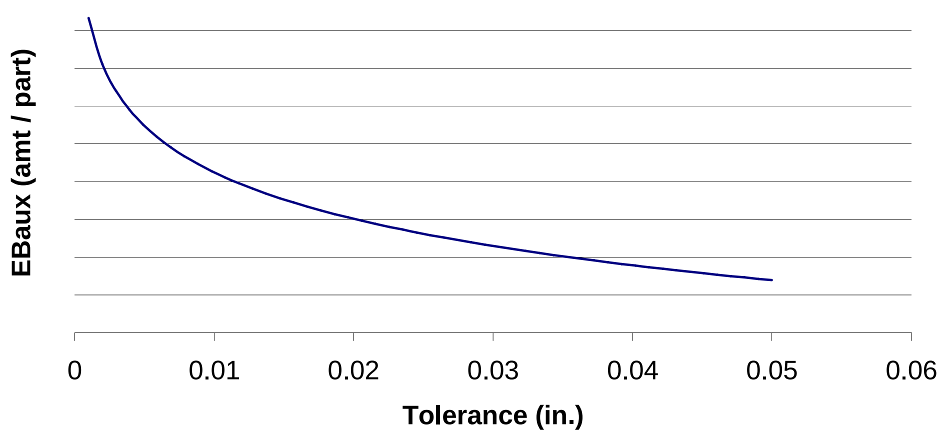


Figure 36 Auxiliary Machine Environmental Burden as a Function of Part Feature Tolerance

The environmental burdens generated by an auxiliary machine, and attributed to a unit of production, are again seen to be inversely related to part feature tolerance. However, the relationship is no longer simple and linear as previously discussed and presented. This situation is due to the non-linear relationship between processing time and feature tolerance. Given the examination of two non-linear processing time – feature tolerance relationships and the resulting form of environmental burdens as a function of feature tolerance a generalization may be made: the exact forms of the primary and auxiliary machine environmental burdens as a function of feature tolerance are wholly dependent on the form of the processing time – feature tolerance relationship. The model for processing time as a function of feature tolerance is substituted directly into the environmental burden model, and the shape of the environmental burden curve as a function of feature tolerance thus takes on that same shape as the processing time – feature tolerance curve.

Considering Support Limits of an Auxiliary Machine

Auxiliary machines are not capable of supporting infinite production rates and numbers of primary machines. In order to operate sufficiently well in a high volume production environment the capabilities of auxiliary machines must be known. As part feature tolerances become looser, processing times decrease, and thus the production rate increases. An auxiliary machine can support a certain amount of primary production, either from one or many primary processing machines. Say that an auxiliary machine can handle up to 180 parts per hour produced by primary machine(s) it supports. If the *HPR* increases above this level, additional auxiliary machine(s) are needed. For the assumed range of *HPR*, resulting from assumed processing times at the boundaries of primary machine's tolerance capability, the number of auxiliary machines as a function of supported *HPR* is given in Figure 37.

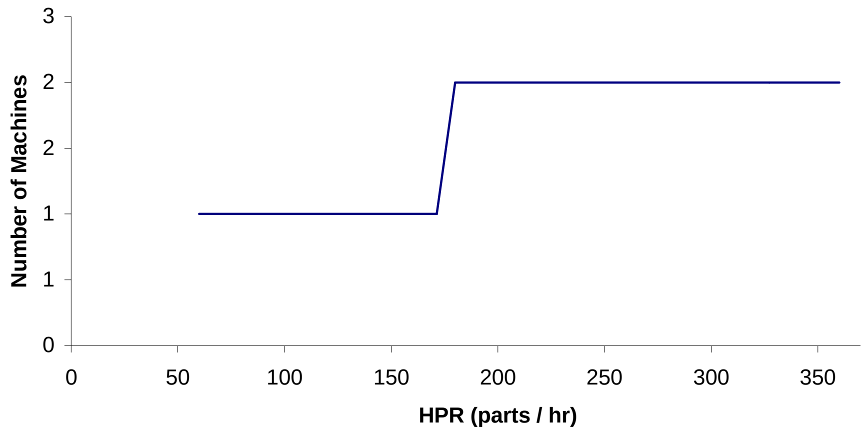


Figure 37 Number of Auxiliary Machines vs. HPR Capability

The trend in Figure 37 is opposite to that of the primary machines (i.e., number of primary machines increases with decreasing *HPR*), and thus when considering primary and auxiliary process performances jointly these may have somewhat offsetting effects on overall manufacturing performance. Heaviest weighting will be given to the primary machines in decision making however, as the final quality of produced parts is of utmost concern. The jump in Figure 37 to an additional auxiliary machine will have cost and environmental performance implications; costs will increase due to the increased initial acquisition cost and the increased costs associated with operating and supporting an additional production machine. The effect on environmental burdens, and thus environmental performance in manufacturing, may be determined by recalling Equation 8. The number of machines in this equation relating processing time to environmental burdens is a multiplier the amount of environmental burden generated per machine. Knowledge of the ‘jumping point’ in Figure 37, along with assumptions of constant environmental burden rate and linear processing time – feature tolerance relationship, the environmental burdens of an auxiliary machine as a function of feature tolerance is plotted in Figure 38.

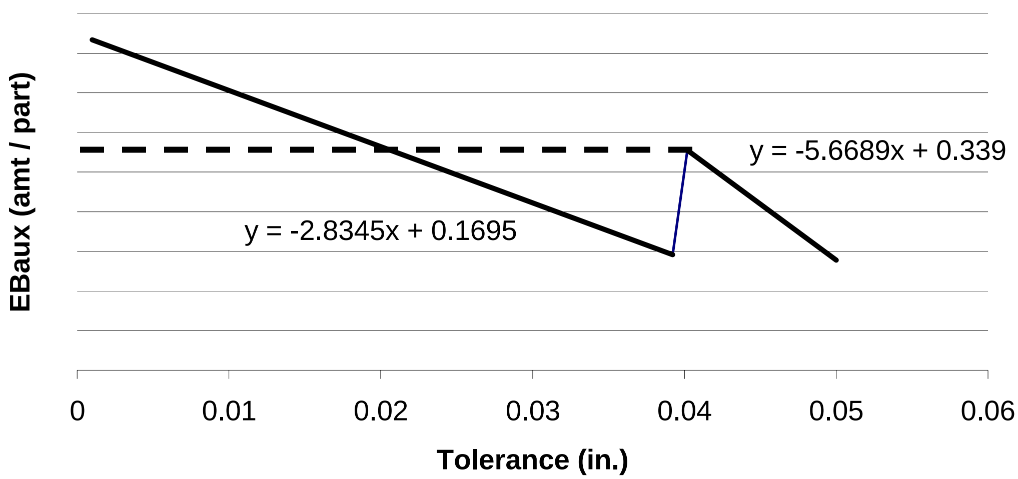


Figure 38 Auxiliary Machine Environmental Burdens as a Function of Feature Tolerance, Considering Limits on Auxiliary Support

The shape of the curve in Figure 38 is not as simple as the one shown in Figure 34. The relationship is still linear, though there are now jumps, or discontinuities, at those tolerance levels which drive the addition of another auxiliary machine. The specific coefficient and constant values of the linear models shown in Figure 38 are not important; however, it is noted that these values are multiples of each other related by the number of auxiliary machines required to achieve production volumes for a given part feature tolerance. It is interesting to note that due to the different number of auxiliary machines required at different feature tolerance levels (and thus primary production rates), that the feature tolerances of about 0.020in. and 0.040in. have the same environmental performance, as measured by amount of environmental burden associated with auxiliary machinery. In fact it would desirable to have a tighter feature tolerance in the range 0.020in. and 0.040in. versus a tolerance setting of 0.040in. because the environmental performance is better! This equivalent performance level is indicated with the dashed horizontal line in Figure 38.

Essentially in this situation the environmental performance of an auxiliary operation in a manufacturing process *improves* in a range of tightening part feature tolerance. This performance gain however will most likely be offset by the degrading environmental performance with tightening of part feature tolerance levels seen in the operation of the primary machine which the auxiliary machine supports. Additionally, there is another tradeoff involving the increased financial costs, and thus decreased manufacturing cost performance, of adding machinery to the manufacturing process. Each machine added increases the initial acquisition costs of the manufacturing process, and also the yearly costs for consumables and maintenance. Though environmental performance gains may be seen in the auxiliary process for tighter part feature tolerance levels, the worsening in both primary process environmental performance and overall cost performance as feature tolerances become tighter will practically undo any auxiliary process environmental performance gains.

The manufacturing performance, in terms of environmental burdens generated, for primary and auxiliary machines as a function of feature tolerances has been discussed in these sections. The parametric study of the manufacturing performance models will now wrap up with a look at traditional machine costs and direct labor, and the aggregate performance indicator models.

3.4.3.3 Traditional Machine Costs and Direct Labor

The cost estimation models do not use processing time as the driver for calculation, except for costs for utilities purchase and by-products disposition, which are converted from activity based environmental burden estimates. In other words, cost is not estimated in an activity based fashion. However, costs are expected to increase with tolerances as more precise (and more expensive) machinery and tooling is required for (additional) manufacturing process steps needed to reduce part feature variation, and thus achieve tighter part feature tolerances. Cost performance in manufacturing, as modeled here, is primarily a function of the selection of the process and machinery, and except for utilities and by-products (which are quite small relative to other machine costs), not the machinery operation.

However, as discussed previously, tighter tolerances will increase processing times and reduce production rates. In order to still meet required production volumes, additional processing machinery becomes necessary, and the addition of machines will increase costs, and degrade manufacturing cost performance. For the example introduced in Section 3.4.3.1 where 180 production parts are required per hour, and *HPR* of primary machines ranges from 60 to 360, given processing times required to meet specified feature tolerances, machine costs as a function of feature tolerance may be determined. It is assumed that yearly tooling, yearly consumable, and acquisition costs, along with direct labor rate, are constant across feature tolerance requirements. Additionally, for the addition of each primary machine, it is assumed that an operator is added. Direct labor is not likely to increase by this much, but more complex production processes will require more operators, maintenance, technicians, supervision, etc. In this production situation and under these assumptions, cost performance in manufacturing, measured by financial costs per unit of production, as a function of feature tolerance is given in Figure 39.

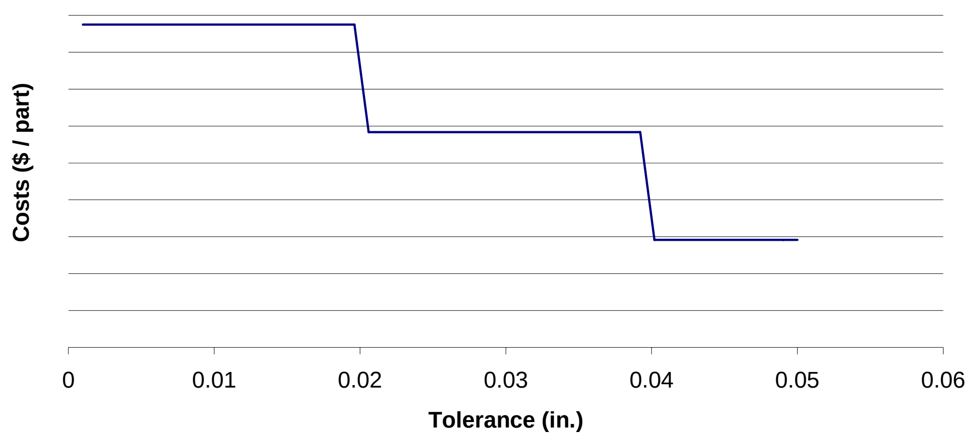


Figure 39 Per Part Machine Costs as a Function of Feature Tolerance

In Figure 39 there are steps and increases in costs as machines are added, but at each step the cost is constant. Identifying the location of the steps in the range of feature tolerance is critical; for stringent tolerance requirements, it would be desired to approach the tolerance limit at a given step, and not unnecessarily require the addition of more production machinery by unwittingly going past the limit. In Figure 39, the tolerance limits where jumps in machine numbers occur are 0.020in. and 0.040in. In this example, one instance of primary machine has been assumed capable of meeting all the tolerances in the given range, from 0.001in. to 0.050in. Not considered here are the jumps to other types of primary machinery, be it from other machine vendors or other machine models, which may be necessary to achieve part feature tolerance outside the capability range of a given primary machine. For example, say another primary machine has a tolerance capability range of 0.005in. to 0.050in.; for part feature tolerance requirements less than 0.005in. this primary machine may not be used and another, likely more expensive, primary machine is required.

The various manufacturing operating costs have previously been assumed as constant as a function of part feature tolerances. This assumption is most likely correct, but it may be expected that tooling costs will not be constant as a function of required feature tolerance. For tighter tolerance more precise (i.e., expensive) tooling is required, and it is likely that more tooling will be consumed in production because of shorter tool life and / or more frequent tool replacement. Assuming that yearly tooling cost to achieve the tolerance limit of a primary machine is twice that of upper tolerance bound, and that yearly tooling cost increases linearly with the tightening of feature tolerances, Figure 40 is given.

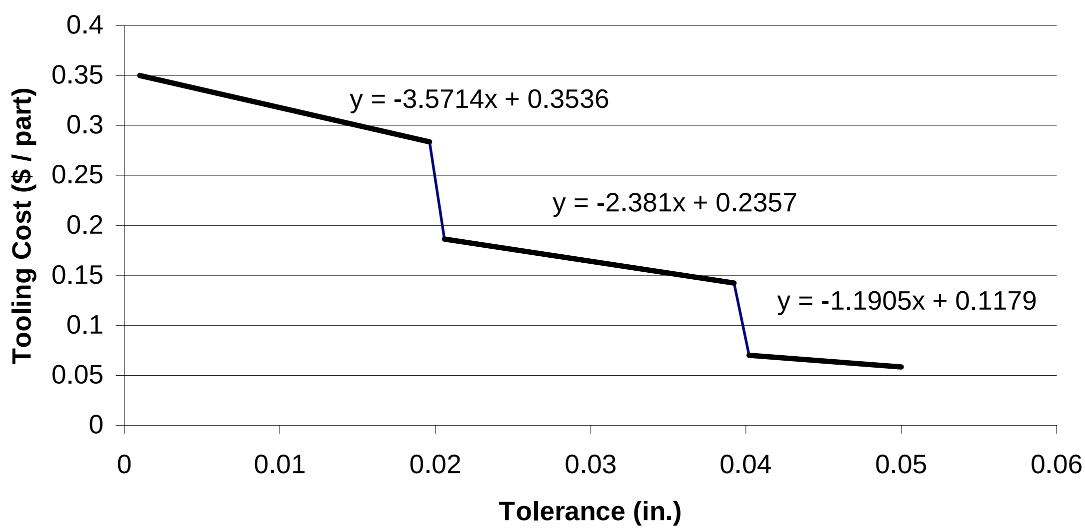


Figure 40 Per Part Tooling Cost as a Function of Feature Tolerance

In Figure 40, jumps due to the addition of primary machines occur at the same points as in Figure 39. Now however the steps are no longer horizontal, but have negative slopes indicating and increase in per part tooling cost with the decrease (i.e., tightening) of part feature tolerance. Again, the constants and coefficients of the linear models in Figure 40 are not important here, but it should be noted that they are multiples of each other related to the number primary machines required at the production level. If the relationship between yearly tooling costs and feature tolerances are not simply linear as assumed here, the shape of the steps in Figure 40 will reflect the shape of that relationship.

3.4.3.4 Aggregate Manufacturing Performance Indicators

The indicators of manufacturing performance that are outputted from the method are aggregated, lump sum values. Forming the inventory portion of the method, environmental burdens from all primary and auxiliary machines are summed within their machine type categories, and then summed again to yield the total amounts of environmental burdens for a manufacturing process. The summed, total environmental burdens of a manufacturing process, as a function of a particular part feature tolerance may be easily found by summing the primary and auxiliary machine environmental burdens as a function of that feature tolerance. Again assuming a linear relationship between processing time and part feature tolerance, for the situation where 180 parts are required per hour from the primary process, and an auxiliary process is capable of supporting up to 120 parts per hour before adding another machine, the total environmental burdens of the manufacturing process are found for a part feature tolerance using the following method.

- Environmental burdens are determined as a function of feature tolerance for the primary and auxiliary machines, and the jumps in numbers of machines considered. These plots are given in Figure 41.

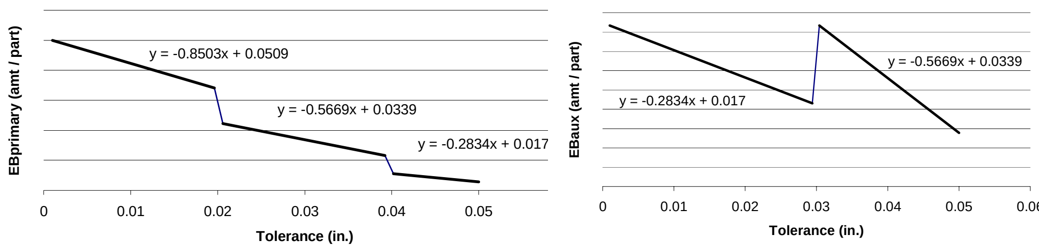


Figure 41 Environmental Burdens of Primary (left) and Auxiliary (right) Machines as a Function of Feature Tolerance

- The plots in Figure 41 are then summed and yield the total environmental burden of the manufacturing process. This plot is given in Figure 42.

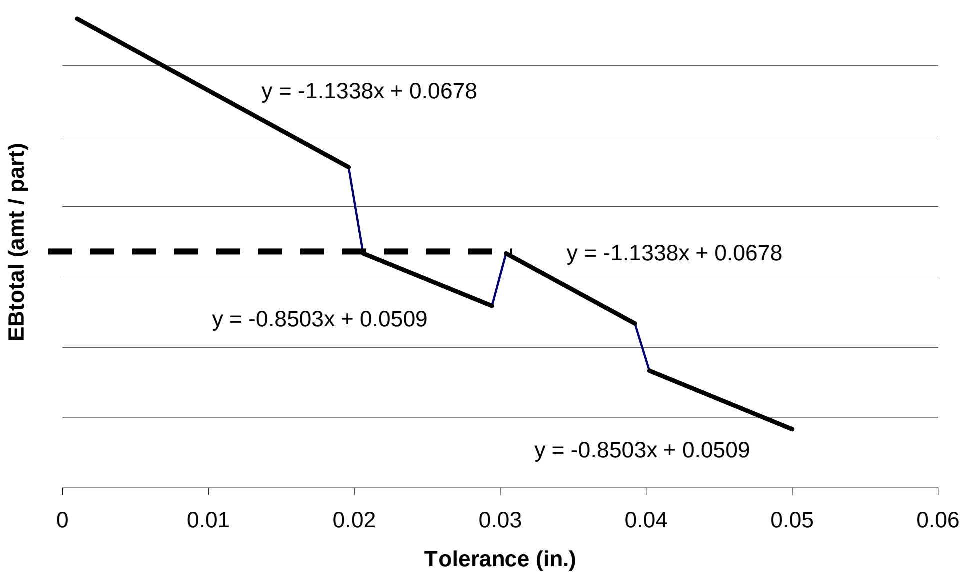


Figure 42 Total Environmental Burdens of a Manufacturing Process as a Function of Feature Tolerance

In Figure 42 it is again seen that environmental burden increases with tightening of feature tolerances. The jumps in the linear trend are due to the addition of production machinery at different production rates driven by the tolerance specification and ensuing processing time. It is interesting to note that the environmental performance of a manufacturing process to meet feature tolerances of 0.030in. and 0.020in. are equivalent, and thus some improvement in environmental performance would be realized in this situation by specifying a tighter feature tolerance in the range of 0.020in. and 0.030in., and not 0.030in. Further there are other equivalent environmental performances in the tighter range of 0.020in to 0.030in., and the looser range of 0.030in. to approximately 0.037in. This trend is for a generic environmental burden of a manufacturing process; within a manufacturing process there will be numerous environmental burdens involved and these curves may be found for each one. The specific quantities and slopes will be different, and determined by process operation specifics, the behaviors will be identical to those discussed in this section.

Determining the shape of the environmental burden curves as a function of feature tolerance is the key step towards quantifiably understanding the relationship between manufacturing performances and part feature tolerances. From the inventory of environmental burdens generated in the method, other important indicators of manufacturing performance are found. The indicators of environmental impact single point score (SPS) and financial cost of environmental burdens (i.e., utilities and by-products dispositions) are calculated using constant eco-indicator values and cost rates. Thus the curves for SPS and these financial costs will follow the environmental burden – feature tolerance trend and form, though the exact curves will differ due to the specific multiplier values. Mentioned previously, but worth repeating, is that the form (e.g., linear, exponential, polynomial, logarithmic, etc.) that the processing time – feature tolerance curve takes will solely determine the specific shape of the environmental performance – feature tolerance curve. This processing time – feature tolerance curve, assumed here for the purpose of exercising the environmental burden models, is highly empirical, but should be found to most accurately connect and relate specific part feature tolerance decisions to manufacturing performances.

3.4.4 Improving the Accuracy of Performance Estimates

A few important steps are necessary to improve the accuracy of the estimates of the cost and environmental performance of the proposed manufacturing process. Taking as many of these steps as possible will ensure that the estimates from the method are most representative of the manufacturing process in reality. As a product design progresses and becomes more well defined, aspects of its process plan may become more well defined also, and improvements to estimated performances possible. In Figure 43 the feedback of information from defined and implemented process plans, and actual manufacturing operations and performances to elements in the method is depicted.

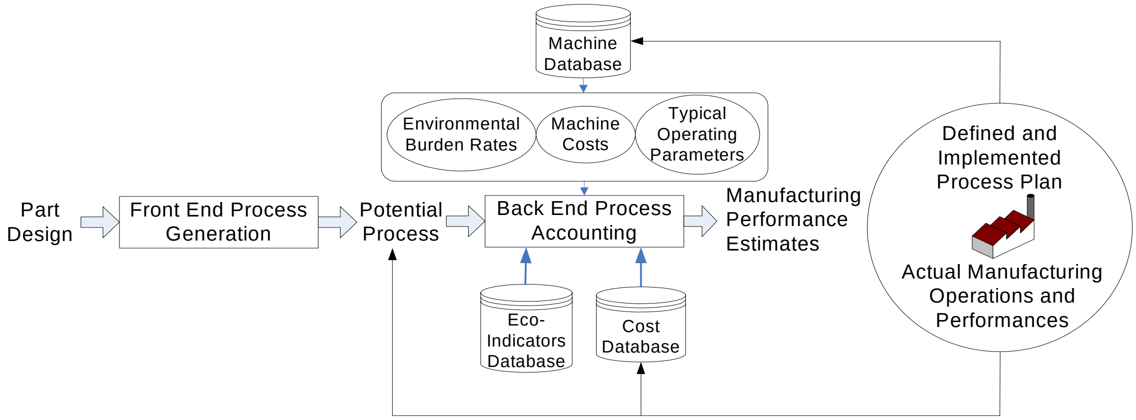


Figure 43 Improving the Accuracy of Performance Estimates via Feedback

When the process plan is defined and implemented the use of the tool is as an assessment; the actual machine configurations (i.e., numbers and sharing), operating parameters (i.e., batch sizes and processing times), some environmental burden rates (e.g., energy usage from initial machine try-out and qualification) and some costs (i.e., machine acquisition, predicted tooling, support materials costs) are known well. As the process is run in actual steady-state production its performance may be better characterized and the actual environmental burden rates, cost rates, machine costs, and operating parameters may be fed back and stored in the method's databases. The purpose of the feedback of all this information is to improve the prediction capabilities of the method when applied to future product design and manufacture tasks, and similar production processes are replicated. In the next sections specific steps to improve estimated manufacturing performances are given.

3.4.4.1 For Primary Machinery

For the primary machines a number of inputs parameters may be 'tweaked' that have direct bearing on calculating estimates and will drive improved results. These parameters are:

- Quantities of each primary processing machine, and fractions of sharing if applicable;
- Machine processing times;
- Machine batch sizes.

Determining the specific processing times as a function of part feature tolerance, a key input parameter for attributing cost and environmental performance to units of production, discussed in the previous section, is not explicitly included in this method, but when processing times are determined elsewhere they may be inputted. For specific part designs processing times may be determined using (1) CAM software, (2) conventional techniques found in machining textbooks such as (DeGarmo, et al. 1997, Kalpakjian 1997), or (3) time estimation method proposed by Ou-Yang and Lin, and also used by Shehab and Abdalla, in their method for estimating manufacturing costs (Ou-Yang, et al. 1997). An example time estimation method, which may be found in basic machining texts, is given in Equation 48.

$$t = \frac{\text{material removed}}{MRR} \tag{48}$$

In Equation 48 *MRR* is material removal rate (with units of volume per time; e.g., m^3/s) found by multiplying width of cut (unit of length) by depth of cut (unit of length) by feed rate (length per time). To achieve tighter feature tolerances in machining the

MRR is reduced, because the widths and depths of cut and / or feed rates are smaller in order to maximize the precision of a cut. Thus looking at Equation 48, for the same amount of material to be removed, a smaller *MRR* due to tighter part feature tolerance requirements will cause an increase in processing time to make the cuts to remove the material.

The method discussed earlier in this chapter should be used for properly determining the quantity of each primary processing machine when sharing of primary machinery between production lines occurs.

3.4.4.2 For Auxiliary Machinery

For the auxiliary machines a number of inputs parameters may be 'tweaked' that have direct bearing on calculating estimates and will drive improved results. These parameters are:

- Quantities of each auxiliary processing machine, and fractions of sharing if applicable;
- Hourly production rate supported.

The methods discussed earlier in this chapter should be used for properly determining the quantity of each auxiliary machine when sharing of auxiliary machinery between production lines occurs and determining the hourly production rate supported by the auxiliary machinery.

3.4.4.3 A Note on Both Primary and Auxiliary Machinery

Typical, or default / assumed, values for these parameters are contained in the machine databases and used in process calculations. These values however are not necessarily specific to the operation of the machine for the desired part design or reflective of reality. Knowledge of (1) how primary machine operation responds to changing part feature tolerance levels (specifically, processing time), (2) how many of each primary and auxiliary machine are needed to balance the line and achieve necessary throughput, and (3) how machines may be shared by other production lines, is *not explicitly captured or automated* in this method. Yet the user may input his or her knowledge and experience with these items into the tool by manually tweaking parameters.

3.4.4.4 Databases

Updating and revising information in databases is extremely important in guaranteeing accurate (realistic) estimates from the method. The information in databases to monitor and periodically update is:

- typical operating parameters of processing times and batch sizes;
- yearly costs of consumables and tooling;
- environmental burden rates;
- conversion factors;
- facility parameters;
- cost rates;
- eco-indicator values;

From time to time these values change due to technology advances, rising costs and inflation, efficiency improvements, machinery upgrades, establishment of historical data trends, changes in manufacturing operations, improved information availability, and general reductions in uncertainty. As new machines are used in steady state production operation the information on that process can become very well known and used as a baseline / benchmark to predict other similar manufacturing processes.

When the information to improve accuracy of the results is unknown, such as in the earliest stages of product design, best guesses will have to suffice. When making comparisons between design alternatives, information that is wholly unknown should be held constant so as to 'subtract out' the common uncertainty. The input of process planners and manufacturing engineers is needed as early as possible to help relieve uncertainty and formulate best guesses where little or no information is available.

3.5. Incorporating Uncertainty into Performance Estimation

Performing the estimation of cost and environmental performances of a manufacturing line for a particular part design has significant data and information needs. The data and information required as inputs into the method for estimating cost and environmental performances are most likely not known perfectly well; there will be some uncertainty about the data. This uncertainty may be due to process variability itself (i.e., the aleatory uncertainty which is due to inherent random or stochastic behavior) and / or imprecise knowledge of the machine or process operation (i.e., epistemic uncertainty which relates to lack of knowledge about reality) (Aughenbaugh, et al. 2004). The distinction between aleatory and epistemic uncertainty is an important one; the stochastic nature of aleatory uncertainty allows the use of probability density functions (pdfs) to describe it while it is incorrect to do so for epistemic uncertainty because the lack of knowledge is not random or stochastic, rather it is systematic (Aughenbaugh, et al. 2004). A manufacturing process is not strictly deterministic and some insight into the sensitivity and uncertainty of performance estimates is necessary to support rational decision making.

The uncertainty analysis is accomplished using Monte Carlo simulation, which has also been applied to other environmental modeling studies where uncertainty is present (Emblemsvag, et al. 2001, Skeffington 2006). Here it is implemented in MS Excel with @RISK software from Palisade Corporation. This software allows for the assignment of distribution information to inputs within an Excel based model. For inputs with epistemic uncertainty where no knowledge exists regarding a possible shape of its distribution, a uniform distribution is defined where all values within a range are equally probable. It is also suggested that a triangular distribution may be used if a central value most expected (Skeffington 2006). Epistemic uncertainty is infinitely reducible in theory, but a point is reached where the cost of the information gained through additional study outweighs the benefits of that information (Aughenbaugh, et al. 2004). For inputs with aleatory uncertainty, a distribution may be defined as normal or some other empirically fit shape.

Monte Carlo simulation involves running the model hundreds or thousands of times and input parameter values are sampled within their defined distributions, either randomly in a pure Monte Carlo sense, or with Latin Hypercube sampling which is more efficient in terms of computer time. For each set of samples in an iteration the output results are computed and recorded. The result of the simulation is a distribution for each output that has a sample mean value and some shape or spread. This type of result is more insightful than a deterministic result as they have incorporated the uncertainty of parameters directly into the model, and thus show the resulting uncertainty of the output.

Knowledge of the uncertainty of the results is helpful towards understanding the risks involved with making decisions based on those results. The sensitivity of the outputs to individual, uncertain inputs is also easily ascertained from the software and is helpful towards identifying the most significant inputs.

One of the greatest benefits of using uncertainty analysis is the generation of a distribution or range for performance estimates. Estimating a range for performance estimates not only gives insight into the variability or uncertainty of those performance estimates, it is much *easier* to estimate a range of values rather than a single point estimate (Rush, et al. 2000). Where it is difficult, expensive, or perhaps even impossible to represent input information required for performance estimates as singe values, and thus achieve single point performance estimates, uncertainty analysis is a valuable tool.

3.6 Thesis Roadmap

The detailed operation of the proposed method has been laid out in this chapter. The requirements for a method, their impacts on the method, the structure of the method and the workings of its two sections, the mathematical modeling of primary and auxiliary manufacturing processes, ways to improve accuracy of results, and the important inclusion of uncertainty were all discussed. Continuing on to Chapter 4 where the significant role of databases is explained, Empirical Structural Validity is further established.

CHAPTER 4

METHOD DATABASES

In this chapter the important role of databases in the proposed method for predicting the environmental and cost performance of a manufacturing process to achieve a specific part design is discussed. The detailed working of the method has already been presented in Chapter 3; the details of components of the databases are fully explained here. Comparing Figures 10 and 12 in Chapter 3, the various information inputs to the predictive model are moved to databases from where they may be accessed when needed for analysis. A particular instance within the machine database, a machine, has the attributes of process capabilities, costs, operating parameters, and environmental burden rates; the following sections describe each of these attributes. Ways to determine the environmental burden rates needed to populate the databases are also discussed. Additionally, the costs and eco-indicators databases, along with a discussion on flexibility in the databases are presented.

The databases are perhaps the most important component of the proposed method. Incorrect or inaccurate information in the databases will cause the most accurate models to yield wrong results; performance estimates generated by the proposed method are only as accurate and / or valid as the data that has been inputted (Rush, et al. 2000). Thus care should be taken in creating, populating, and maintaining them.

It is a goal of this thesis to show value in the existence of machinery databases with respect to the capability to predict manufacturing performances in the context of design for manufacturing decision making. Besides this potential benefit, the creation and maintenance of machine databases may be advocated based on the tendency of manufacturers to replicate and reuse production equipment on other production lines of similar part types (i.e., part families?). Machine selection is primarily a business decision influenced by history and relationship with machine vendors and manufacturers. Machines with known quality and ability to produce satisfactory parts can reduce manufacturing costs and headaches associated with qualifying completely new machinery. The reuse and standardization of machinery and processes reduces process planning complexity significantly by shrinking the selection pool, and thus detailed knowledge of both the cost and environmental aspects of machinery that is proliferated throughout the manufacturer's facilities is valuable.

A Note on Uncertainty

For information in databases that is uncertain or variable, those parameters should be modeled either as a uniform distribution with lower and upper bounds on the range, or as a normal or some other empirically fit distribution. The information that will commonly be uncertain and / or variable is:

- Operating Parameters: processing time
- Costs: yearly tooling, yearly consumables, utility and consumable rates, by-product rates, labor
- Environmental Burden Rates: utilities and consumables, by-products
- Facility Parameters: number of operators, yearly production

4.1 Machinery Databases

Recalling Figure 10 in Chapter 3, it is seen that a predictive model of manufacturing performances requires significant amounts of information. The bits of information specifically related to machinery are environmental burden rates, typical operating parameters, machine costs, and process capabilities, for each available machine; this data and information is to be placed databases of primary and auxiliary machines and is depicted in Figure 44.

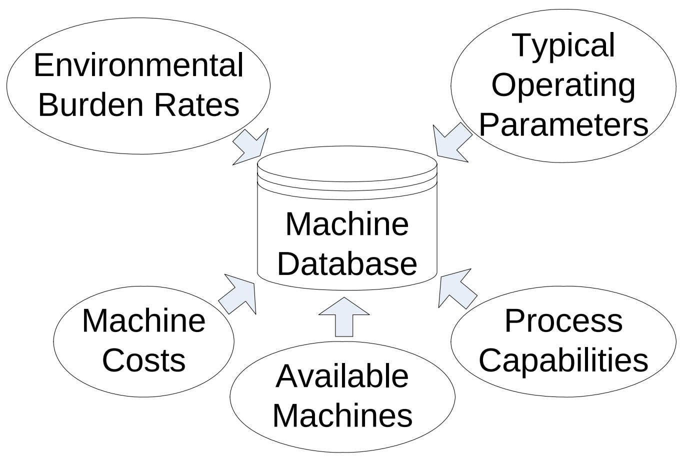


Figure 44 Machine Database Inputs

Each of the inputs to the machine database of Figure 44 will be discussed in detail, and the implementation shown, in the next sections. More on the actual implementation of the machine databases in the developed Excel-based tool is given in Appendix A and in (Bradley 2006).

4.1.1 Process Capabilities

Process capability is the scientific and historic knowledge of individual manufacturing operations (Chang 1998); specifically, this is the ability to produce part designs in a satisfactory manner. Process capability information exists at three levels: at a universal level, at a shop level, and at a machine level (Chang 1998). Universal process capability information, typically found in handbooks, is generally too abstract to be connected to actual manufacturing processes for producing a part. An example of universal process capability information from Kalpakjian (Kalpakjian 1997) is shown in Figure 45; various general manufacturing processes are on the Y axis and tolerance capability on the X axis. For each process the achievable tolerance range is plotted for average and also less frequent applications.

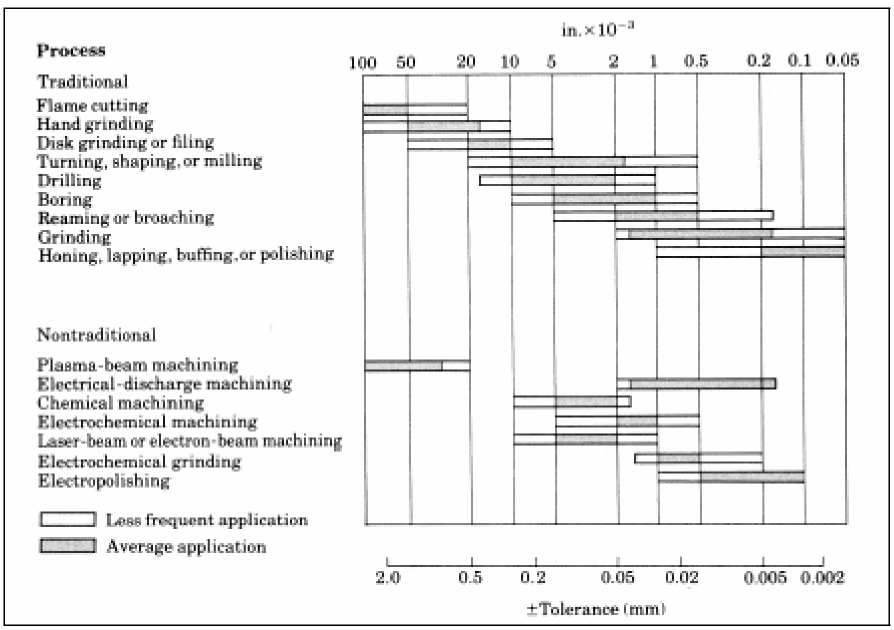


Figure 45 Tolerance Capabilities of Various Processes (Kalpakjian 1997)

Shop level process capability information is at a level of greater process detail and is typically known for individual machine shops or companies. The abilities of a particular shop, production line, or facility are typically known with some certainty. The machine level process capability information has the greatest detail on actual processing by individual machines. The ability of a specific machine to achieve specific goals is addressed by machine level process capability information (Chang 1998). The specific capabilities of individual machines, even of the same kind and / or manufacturer, may vary. Obtaining information at this level of detail, such as for the tolerance capabilities on specific part features, is not trivial and requires experimentation, data gathering, and analysis.

It is the machine level of process capability information which is desired to populate the machine database. Populating the database with detailed information better allows for more automated generation of potential processes from part designs. Changes in part feature designs can induce discrete switching between potential operations in a manufacturing process flow. For example, say two milling machines are capable of achieving dimensional tolerances up to ±0.005 in. and ±0.001in., respectively. For a part design that requires dimensional tolerances of ±0.010 in. either machine would be suitable and could be implemented in the process. However, should the design require dimensional tolerances of ±0.003in., only the 2nd milling machine is capable and would be implemented in the manufacturing process. The process capability portion of the primary machine database, as implemented in the Excel-based tool discussed in the next Chapter, is given in Figure 46. For a given primary machine, up to 10 features the machine creates may be listed, and for each feature the lower bound on dimensional capability (DL), the upper bound on dimensional capability (DU), and the tolerance limit (TL) may be specified and housed in the primary machine database. These important process capability values are used in the if…then primary machine filtering operation of the front end process generation component of the method.

Machine	Features Created	DL	DU	TL
Machine 1	1			
	2			
	3			
	4			
	5			
	6			
	7			
	8			
	9			
	10			
Machine 2	1			
	2			
	3			
	4			
	5			
	6			
	7			
	8			
	9			
	10			

Figure 46 Process Capabilities Section of Primary Machine Database

If other methods of generating potential processes are employed, reliance on this great level of machine-specific process capability is reduced or eliminated. This is often necessary because machine level process capability information often is unknown and even impossible to know, particularly for new production machinery or the production of new parts. Where no historical information exists for process capability, other levels of process capability information and human experience and expertise must be used to guide process generation.

An open question, and something not explicitly addressed in this method, is the following: *How does machine performance change within the process capability spectrum?* For example, consider a hypothetical milling machine which is capable of producing slot features with a depth between 0.05 in. and 0.50 in., with a tolerance limit of 0.001 in. and tolerance upper bound of 0.050in. It may be expected that the machine's operation (and thus performance) to produce different slot designs with depths within the dimensional capability spectrum (0.05in. to 0.50in.) and with different tolerance precision requirements will not be exactly the same. The difference in machine operation may be abstracted into the processing time which in turn may be used by the method for performance estimation, as discussed in Chapter 3. However, machine operating characteristics (e.g., tooling use, consumption of utilities, by-products generation, etc.) are assumed to be constant within the spectrums of dimensional and tolerance capabilities. This assumption may be valid, but empirical study is required to confirm that performance is indeed constant and does not exhibit some other behavior with a machine's capability spectrum such as linear or exponential. This situation is depicted in Figure 47 below; as is in the method machine operation is assumed to be constant across the process capability spectrum of a primary machine, but may take another shape indicated by the dashed curves in the figure. If the machine operation characteristics are not constant within these range of process capabilities, the specific machine characteristics for a desired dimension and tolerance specification must be manually inputted into the method so as to most accurately generate manufacturing performance estimates.

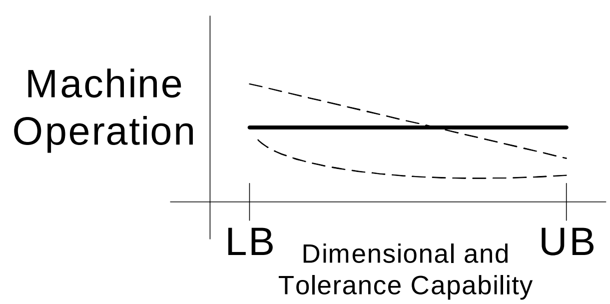


Figure 47 Machine Operation Across Process Capability Spectrum

4.1.2 Environmental Burden Rates

Environmental burden rates are the rates of utilities and resource use and by-product generation (e.g., kW of electrical power and lb / hr of wastes). The steady state rates are considered here and assumed to be the most significant, though the environmental burdens of start up and shut down (e.g., flushing a washer tank) (Román, et al. 2006), and preventive maintenance operations could possibly be significant. The environmental burden rates included in the machine database as baseline are the following:

- Energy: electrical power (kW), compressed air (cfm), and could also include other energy sources such as natural gas (cfm) and steam use (lb/hr) for operations such as heat treatment and part washing;
- Resources: water use (gph);
- By-product generation: landfillable wastes (lb/hr), recyclable materials (lb/hr), and special or hazardous wastes (lb/hr) which require more costly handling and treatment.

The sections of the primary and auxiliary machine database which contain the environmental burden rates are shown below in Figures 48 and 49, respectively.

19			Environmental Burden Rates				
Primary	Utilities and Consumables					By-products	
Machine	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)
Machine 1							
Machine 2							

Figure 48 Environmental Burden Rates Section of Primary Machine Database

	A	D	E	F	G	H	I	J
1	12	s						
2				Environmental Burden Rates				
3	Auxiliary		Utilities and Consumables				By-products	
4	Machine	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)
5	Machine 1							
6	Machine 2							
7								

Figure 49 Environmental Burden Rates Section of Auxiliary Machine Database

For operations with waste streams beyond these three general categories, and / or with multiple material types within a particular waste stream, the generation rates for each are required to properly account for environmental impacts, even though the financial cost for disposal may be equivalent. Similarly, for operations that use other energy sources and / or resources not listed here, individual usage rates are required to account both environmental impacts and financial costs. The determination of environmental burden rates is typically not a simple exercise; the next section discusses methods for determining environmental burden rates.

4.1.2.1 Determining Environmental Burden Rates

The environmental burden rates of individual machines will not always be available. Environmental information and data for machines are missing for a couple of reasons: (1) lack of monitoring or measurement at machine and process levels; (2) where tracking does occur, it is decentralized; that is, information exists, but the dispersion of the information among different groups and personnel makes access difficult; and (3) the diversity of processes that are housed within a plant make the deduction from plant level information of specific process or machine level information practically impossible. However, when this information is known, it may be inputted into the tool to achieve more accurate results.

Addressing the reasons behind the unavailability of environmental information for machinery, methods for determining environmental burden rates are proposed.

- Installing meters on individual machinery, though potentially costly to a manufacturer, would improve the traceability of machine level environmental data; the following environmental burdens could be better measured by metering individual machines: electricity, compressed air, steam, natural gas, water, and possibly by-products and wastes generation. Meters do not necessarily need be installed permanently; remaining in place long enough to characterize performance is sufficient.
- Requiring machine manufacturers to better incorporate environmental performance monitoring on machines would be helpful. Modern manufacturing machines have on

board computer systems that control, track, and monitor machine operation and communicate with other computers in the manufacturing environment over a network. Processing times, uptime, and tool life are a few of the operating characteristics typically in the scope of these computer systems; machine vendors and manufacturers could perhaps better incorporate environmental performance monitoring with the more traditional operation monitoring on their machines than a manufacturer using the machine and installing their own meters. Machine level information could be fairly well known with this level of data collection.

- Monitoring and sampling of steady state use or generation on some time-basis is the most direct method for determining environmental burden rates. For example, weighing wastes before disposal and noting frequency. With these manual or direct determinations of environmental rates repeated samplings allows for the generation of statistical distributions that may be used to capture the uncertainty and variability of the rates which are used as inputs to the model.
- Storing environmental data generated in internal web-based databases that are accessible by those within the organization who need it would improve accessibility of environmental burden rate data. The organizational issues of decentralized and distributed data are difficult to address well in a short space and are outside the scope of this thesis. With metering and computer-based monitoring of environmental performances of machinery and processes, much data could be generated and collected. The issue is determining what to do with all that data; an obvious solution is storing it in internal web-based or intranet accessible databases that are accessible by those within the organization who need it.

- Examining machine documentation and other vendor supplied literature on machine performance and operation is often the best start towards determining the environmental burdens rates. The values found herein are likely to be somewhat different from those in a specific production environment.

For example, for many machines a 'full load amperage' is specified in documentation. This is the amount of line current drawn by the machine's motors at rated load and voltage. This value is a start towards knowing the electrical energy use of the machine, but is likely too high since machine operation is not likely to be at rated load in the steady state. For 3-phase supply, standard in the US, and known voltage, the electrical power may be computed using Equation 49, found in any electrical engineering textbook.

$$P_{\text{electrical}} = pf \times \sqrt{3} \times V \times FLA \times \frac{1\,\text{kW}}{1000\,\text{W}} \tag{49}$$

Where in Equation 49 √3 is related to the phase angle between voltage and current sine functions, and *pf* is the power factor, typically around 0.9. For a hypothetical machine with a full load amperage of 60 A with a 3-phase supply at 230 V, a first estimate for the power requirement of the machine may be found to be 21.51 kW, using Equation 49.

P_{elec} = (0.9) * √3 * 230 V * 60 A * (1/1000) = 21.51 kW

Machine operating performance with respect to utilities use may be assumed to relatively constant regardless of the part design under production, assuming the same material, of course. However, the generation of by-products (wastes, sludge, metal chips for disposal or recycle, etc.) is highly dependent on the part size, amount of material to be removed, and blank size. Thus for estimating manufacturing performance with this proposed method, it is desired that machine information be used from a database created for production parts that are relatively similar in size and material removed. This situation is very important when interpreting estimates for by-product and wastes generation, and must be manually considered in this method.

The diversity of processes that are housed within a plant make the deduction from plant level information of specific process or machine level information practically impossible. This diversity of processes housed in manufacturing facilities is not likely to decrease and thus the deduction of process or assembly level environmental information from plant level information is not likely to become easier. Manufacturing environmental information may be thought to exist at three levels of abstraction (or dimensions); plant level, process level, and machine level. These levels are depicted below in Figure 50.

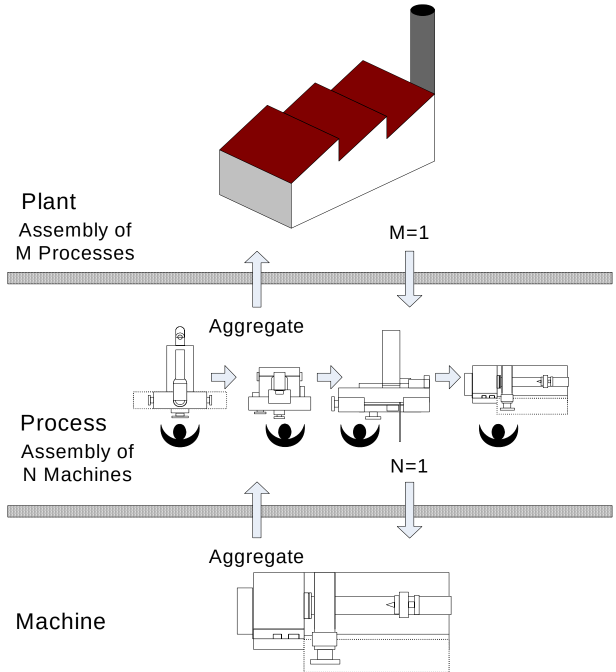


Figure 50 Multi-dimensionality of Manufacturing Data

Building up from the machine level, a process may be thought of as an assembly of N machines aggregated. Aggregating further, a plant may be thought of as an assembly of M processes. If N or M were to equal one, the levels of abstraction would collapse and the process would be the machine, or the plant would be the process. Understanding this hierarchy is useful towards better deducing lower level environmental information from a higher level of abstraction, and also how higher levels are rolled up from lower levels. At each level there exist energy and mass flows in and out; quantifying them and determining their flow rates is of interest.

Processing Time vs. Cycle Time

As explained previously, the mathematical models use processing time as the chief input parameter that drives the calculation of environmental burden estimates;

processing time may be defined as the amount of time a part is under operation by a machine. Different tolerances levels can be expected to affect processing times; tighter tolerances would likely require longer processing times on the same machine due to reduced depths of cut, more cutting passes, lower feed rates, etc. necessary to achieve tighter tolerances.

The use of processing time in the mathematical models requires ***steady state*** generation or use information. Steady state generation or use information is the machine performance while processing a workpiece, and does *not* include the performance of the machine while idle or transferring parts. The environmental burden rates in the machine database have time bases of either hours or minutes; these rates need to be the amount of generation or use for a whole minute or hour, whichever applies, of processing by the machine. This determination will likely require some experimentation and extrapolation. If steady state environmental burden rates can not be ascertained, the use of cycle times may be used, but the models must be changed to reflect this situation.

Cycle time includes wait and transfer times, in addition to processing time, and may be defined as the time elapsed between the start of machine operation on a unit of production to the start of the same operation on the next unit of production. Cycle time is more of a function of line balance and flow, and machine or material handling speed, and does not necessarily reflect the capability of a machine to achieve part feature tolerance levels, or how machine performance changes in response to part feature tolerances.

The use of cycle time in the mathematical models requires ***average*** generation or use information. Average generation or use information is the performance of the machine over some time period, which includes processing time, idle time, and time to transfer parts. This type of machine performance information may be easier to obtain, but is not preferred to the steady state machine performance. If average machine performance information is all that can be ascertained and the primary machine database populated with it, the models must be changed to reflect the use of cycle times.

The difference is subtle between processing time and cycle time and the associated data types, but could be very significant. The correlation of correct model forms with the type of entry in the machine database is important.

4.1.3 Financial Costs

Operating and machine costs are generally well understood by a company and their inclusion in the model is simple. The costs specific to machinery and stored in the machine database are the yearly costs of tooling and consumables, and also the initial acquisition cost of the machine. Auxiliary machines do not directly affect parts under production, do not use tooling, and thus do not have a tooling cost category in their machine database structure. The operating costs are not specific to a particular machine necessarily, but rather to the facility in which a machine is placed. Thus the operating costs of utilities, by-products handling and disposal, and labor are not placed in the machine database but rather in the costs database and facility parameters, respectively. The financial cost sections of the primary and auxiliary machine databases are also given in Figure 51 and 52, respectively.

19	rrect name!!		
Primary		Costs ($)	
Machine	Yearly Tooling	Yearly Consumables	Acquisition
Machine 1			
Machine 2			

Figure 51 Costs Section of Primary Machine Database

Auxiliary	Costs	
Machine	Yearly Consumables	Acquisition
Machine 1		
Machine 2		

Figure 52 Costs Section of Auxiliary Machine Database

4.1.4 Operating Parameters

Operating parameters are the values for particular machines that describe their operation. Operating parameters can be quite detailed, down to the level of the mechanics of cutting operations (e.g., rake angles, feeds, and depth of cut), but are at a higher level in the model. The standard operating parameters required to populate the machine database are typical batch size and processing time.

Mentioned previously, part tolerances have their impact on manufacturing by driving the selection of process machinery and also the subsequent operation of that machinery. The selection of more precise machinery is handled in the process generation step, but process operation warrants more discussion. Tighter tolerances require the operation of production machinery in a more controlled manner to reduce variation. Without knowing the inner workings of individual production machinery, processing time is expected to be the main operating parameter affected by tolerance requirements on a finished part. That is, processing time required will likely be different depending on location in process capability 'spectrum' for a given feature. For the same cutting machine, longer processing times are expected for tighter specified tolerances. Determining the processing time as a function of specified part tolerances, or at least developing a methodology to do so, is vital towards connecting part tolerances and machine operation. The section of the primary machine database which contains operating parameters is shown below in Figure 53.

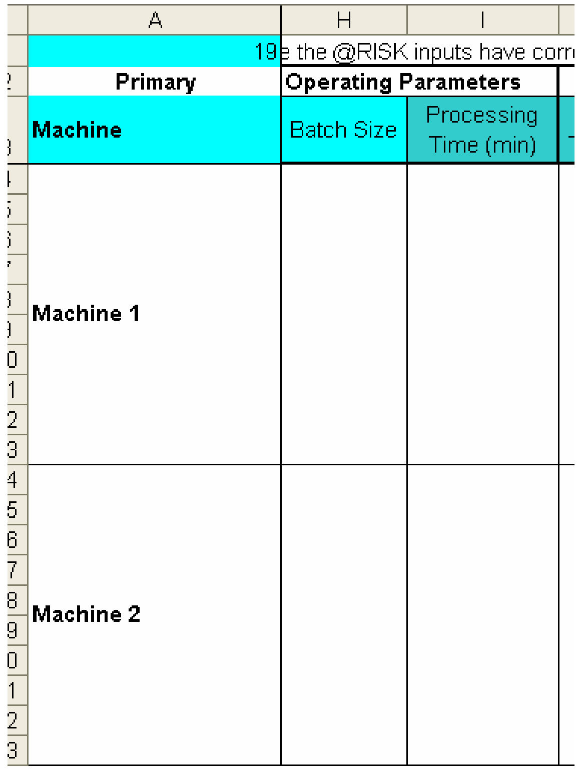


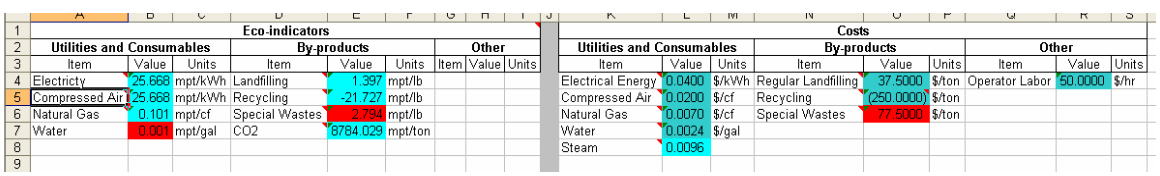
Figure 53 Operating Parameters Section of Primary Machine Database

Each of the major attribute types housed in the machinery databases, for both primary and auxiliary machinery has been discussed. The databases containing the important cost rate and eco-indicator value information will be discussed next.

4.2 Costs and Eco-Indicators DBs

As many entries as are needed may be placed into the databases for costs and eco-indicators. These values are used to convert items in the environmental inventory of burdens into financial costs and environmental impact scores, respectively. Cost rates may be found from internal company sources, the US Department of Energy, utilities companies, and / or service providers. Eco-indicator values were found using SimaPro Life Cycle Assessment software from PRé Consultants. These Eco-indicator values are based on the Eco-indicator 99 scheme, which attempts to distill a full life cycle assessment (LCA) down to a single environmental impact score. Eco-indicator values, in units of millipoints (mpt), are found in the software's database for many materials, utilities, by-products, etc. Models may be needed to derive proper eco-indicator values for specific items encountered in different manufacturing processes, but are not discussed here.

Input from process planners and manufacturing engineers should be sought in determining the correct cost rates and eco-indicator values for the proposed process, unless the product designer is highly knowledgeable of this information. Cost rates may contain uncertainty or variability that can be modeled as by some pdf. Those cost or eco-indicator items that are unknown, best guesses or placeholders should be assumed. The costs and eco-indicators database, as implemented in the Excel-based tool is shown below in Figure 54.



Eco-indicators								
Utilities and Consumables			By-products			Other		
Item	Value	Units	Item	Value	Units	Item	Value	Units
Electricty	25.668	mpt/kWh	Landfilling	1.397	mpt/lb			
Compressed Air	25.668	mpt/kWh	Recycling	-21.727	mpt/lb			
Natural Gas	0.101	mpt/cf	Special Wastes	2.794	mpt/lb			
Water	0.001	mpt/gal	CO2	8784.029	mpt/ton			

Costs								
Utilities and Consumables			By-products			Other		
Item	Value	Units	Item	Value	Units	Item	Value	Units
Electrical Energy	0.0400	$/kWh	Regular Landfilling	37.5000	$/ton	Operator Labor	50.0000	$/hr
Compressed Air	0.0200	$/cf	Recycling	(250.0000)	$/ton			
Natural Gas	0.0070	$/cf	Special Wastes	77.5000	$/ton			
Water	0.0024	$/gal						
Steam	0.0096							

Figure 54 Costs and Eco-Indicators Database

4.3 Flexibility

The specific environmental burden rates contained in the machine databases are by no means exhaustive or complete, but are at a minimum the items which are commonly of concern to manufacturers. The method has the capability to estimate additional environmental burdens that may be of interest for specific manufacturing processes. For utilities and consumables there may be specific energy sources, gases, or fluids that require accounting because of their significant cost, nontrivial or non-negligible amount of use, and / or the use has major environmental or health impacts. For by-products, the specific components of the waste streams or emissions may be wished to be known.

For utilities and consumables a few examples of environmental burdens that could be added to the machine databases and estimated are the following:

- Renewable sources of energy (e.g., electricity from solar power or wind mills);
- Other energy sources such as steam, or the burning of gases like propane and methane;
- Gases such as helium, nitrogen, etc. used in processes;
- Fluids and chemicals such as cutting fluid, cleaning mixtures, hydraulic fluid, etc.;
- Materials and items such as filters, grease, lubricants, etc.;
- Any restricted items.

For by-products a few examples of environmental burdens that could be added to the machine databases and estimated are the following:

- Specific components of landfill waste such as general trash, metal chips, fluids, tooling, filters, etc.;
- Specific components of the materials which may be recycled;
- Specific components of special or hazardous wastes which require special (and more costly) handling;
- Any by-product which must be specially handled;
- Generation of other harmful emission such as methane, nitrous oxide, HFC’s, etc.;

- Release of VOCs;
- Any restricted items.

Determining which environmental burden rates to monitor and estimate is left to the user of the tool, who may be guided by his or her company's practices and policies. Items that should be included are those whose use is significant and nontrivial in steady state production operation. Gauging trivial from nontrivial is admittedly subjective, but the relative amounts, costs, and impacts in a process may be a guide.

4.4 Thesis Road Map

The detailed operation of the proposed method has been laid out in Chapter 3, and in this chapter the important role and details of databases in the proposed method, particularly that of machinery databases, has been given. Specific explanation of each of the attributes in the machine databases, including methods to determine environmental burden rates, along with a brief explanation of the cost and eco-indicator databases, and the inclusion of flexibility in the method and databases has been presented. Combining Chapters 3 and 4, the Empirical Structural Validity of the proposed method has been furthered. The next region of the Validation Square to be examined is Empirical Performance Validity, which involves testing the proposed method by running example problems. Before going to the example problems in Chapters 6 and 7, the instantiation of the method discussed in Chapters 3 and 4, as and Excel-based tool will be discussed in Chapter 5. The developed tool is then applied to example problems.

CHAPTER 5

AN INSTANTIAION OF METHOD AS AN EXCEL-BASED TOOL

In this chapter the instantiation of the method of Chapters 3 and 4 as an Excel-based tool is discussed; the tool has been titled "The Part Manufacture Cost and Environmental Performance Predictor". The developed tool is applied to the example problems in Chapters 6 and 7. The topics to be discussed in this chapter are an introduction and overview of the developed tool, the limitations of the tool, mostly related to the coding of the tool in Excel, and a discussion on interpreting results (the outputted manufacturing performance estimates) from the tool.

5.1.Introduction to Tool

The Part Manufacture Cost and Environmental Performance Predictor is an Excel-based tool for predicting the cost and environmental performances of manufacturing processes required to achieve product designs. Product designs, specifically their part feature tolerances, have strong impacts on manufacturing by driving the selection of particular machinery, and the operation of that machinery; the tool has the capability to address both. Results from the tool are 'built up' by assembling the required primary and auxiliary machinery, and then aggregating the machine level operating performances.

Macros written in Visual Basic are used extensively to automate the tool, with the goal of making the tool's use as easy and straightforward as possible for the user. Today's designers have enough on their plate as is, and the inclusion of cost and environmental consciousness and objectives to product design should not be burdensome.

By providing quick and quantified cost and environmental performance information, product designers gain knowledge of the impacts that their designs will have on manufacturing cost and environmental performance. It is also possible to ascertain by how much these impacts change with potential alternative product designs. With this knowledge, better, more informed, decisions may be made in product design to improve cost and environmental performances in product manufacture.

The uncertainty of parameters associated with operations and machinery is captured through the use of probability density functions and Monte Carlo simulation is performed to develop descriptive statistics for model results of interest. Manufacturing processes are not strictly deterministic and some insight into the uncertainty of the model results is necessary to support rational decision making. @RISK, an Excel add-in for conducting risk analysis through the use of Monte Carlo simulation, is employed.

The intended user is a product designer who: (1) is undertaking Design for Manufacturing (DfM) and / or Design for Environment (DfE) efforts, (2) has good familiarity with the manufacturing processes of his or her part designs, and (3) is working in conjunction with process planners. The input of process planners and manufacturing engineers is vital to the tool and this process, especially in populating and maintaining the databases in the tool and guiding front end process generation. And thus ensuring the most accurate estimates possible. Additionally, process planners and manufacturing engineers will find this tool useful for evaluating potential process designs against cost and environmental objectives.

The main components of the tool are as follows, and are fully explained in the body of the User's Manual, found in (Bradley 2006):

- Front End: Generating a Proposed Process
- Back End: Accounting for a Proposed Process
- Databases
- Including Uncertainty and Variability in Performance Estimates

5.2. Overview of Tool

The developed Excel-based tool is presented in Appendix A of this thesis. There are explanations of each sheet of the two files which comprise the tool, a front end and a back end file, as well as basic instructions on how each sheet is to be used in first generating a potential process plan for an inputted part design, and then accounting that proposed manufacturing process and estimating its cost and environmental performances. Additionally there is a section introducing the user to the use of @RISK, an Excel add-in employed in the developed tool to conduct uncertainty analyses. For more information on the developed tool, a User's Manual is available (Bradley 2006). For more information on using @RISK there is also a guide published by the developer (Palisade 2002). The discussion on the general procedure for using the tool to estimate manufacturing performance may be broken up into two sections; the first being front end process generation and the second the back end process accounting.

Before a process may be accounted it must first be generated. To generate a potential process to produce a part design, a user does the follow:

- Part feature designs, which include feature dimensions and dimensional tolerances, are inputted in the process generation sheet of the tool.
- The filtering operation is done to filter out those available primary machines in the primary machine database which are incapable of producing the inputted part design.

- From the list of machines which passed successfully through the filtering operation, the user must select the desired primary machines for his or her process.
- Alternatively, if the tool is either being used to conduct a manufacturing performance assessment, or the specific part feature design and / or the exact machine process capabilities are unknown, primary machines may be manually selected from a listing of all available primary machines.
- Once the primary machines are chosen by the user via either method, the auxiliary machines to support those primary machines are determined either automatically, using the auxiliary machines specified for a given primary machine in the primary machine database, or manually, by selecting the desired auxiliary machines from a listing of all available auxiliary machines.
- With the primary and auxiliary machines chosen for the potential manufacturing process, machine data and information is next pulled from the appropriate machine database, housed in the front end file of the tool, and then imported by the back end file of the tool for accounting.

Thus, the input to the front end file of the developed Excel-based tool is a part design with its features to be created, and the dimensions and tolerances of those features. The output of the front end file, which serves as the input to the back end file, is a listing of the primary and auxiliary machines of the potential, proposed process with each machine's data and information carried along. To then account that process, a user performs the following tasks in the back end:

- Import the proposed primary and auxiliary machines, along with their data and information, into the back end file of the developed tool.

- Apply the mathematical models in the calculation sheets; estimates for environmental burdens, environmental impacts, and financial costs are generated for all the primary and auxiliary machines.

The indicators of manufacturing performance are reported as aggregate results, and also broken down by major categories such as machine type (i.e., primary and auxiliary), utilities and consumables, or by-products. Also, the slots in the back end file where a user may update important process information, such as processing times (previously discussed) and batch sizes, are clearly defined. Much of the operation of the front end and back end files is automated using macros to make the use of the tool as easy as possible for the user.

The inputs to the back end file are the potential, proposed process from the front end file, and the information and data associated with the primary and auxiliary machines which comprise that process. The outputs from the back end file are manufacturing performance estimates on a per unit of production basis of the proposed manufacturing process: an inventory of environmental burdens, an environmental impact single point score (SPS), and the total financial costs. Each performance indicator may be viewed at different 'levels' in various results sheets; the most aggregated indicators found in the summary outputs may be useful to higher level decision makers, such as managers, while more detailed, disaggregated indicators found in categorical breakdown and calculation sheets may be useful to decision makers closer to the actual manufacturing operation, such as process planners and manufacturing engineers. All the estimated performance indicators out of the back end file are deterministic, single point numerical values. After the back end file is fully run, and the proposed process accounted, uncertainty analysis by Monte Carlo simulation, conducted using @RISK, should be done.

Performing uncertainty analyses with @RISK is fairly straightforward and easily done. As an add-in to Excel, @RISK operates nearly entirely within the Excel environment; there are auxiliary @RISK windows for examining uncertainty models and simulation results, but are all directly tied to the Excel-based models. Inputs with uncertainty simply have a distribution assigned to their cells, and the results of calculations (e.g.., manufacturing performance estimates) on which descriptive statistics are desired are chosen by 'recording' the particular cell. Performing a Monte Carlo simulation with @RISK is done by setting the desired number of iterations, and the sampling method: either purely random or with a more efficient Latin Hypercube. The software performs the simulation, iterating hundreds or thousands of times, in a matter of seconds. Results from the Monte Carlo simulation, and sensitivity analyses, are viewed either in the @RISK Results window, or in a report exported as a new Excel work book.

The developed tool , by quickly generating manufacturing performance estimates using historical machine operating characteristics housed in databases, may be used to get feedback on potential downstream effects in manufacturing that either product or process design decisions may have. With this feedback information product and process designers may be enabled to make better decisions with respect to manufacturing cost and environmental performance goals. While powerful in this regard, there are a few limitations of the developed tool which need disclosure so as to not oversell the tool and its abilities.

5.3. Tool Limitations

There are limitations to the Part Manufacture Cost and Environmental Performance Predictor, primarily related to the implementation and coding in MS Excel.

5.3.1. Size Limitations

In the primary machine database, an infinite number of machines may be inputted into the database. However, the number of inputs for features created by that machine and for required auxiliary machines is limited to **10** for each primary machine in the database. Should there be a need for more than 10 slots for features created by and / or required auxiliary machines for primary machine entries, please contact the developer.

For both the primary and auxiliary machine databases, additional environmental burdens may be added to the database to accurately reflect the processes being modeled. Should there be a need to add more than **25** environmental burdens to the existing list please contact the developer.

The number of machines in the primary and auxiliary proposed processes is limited to **50** unique machine types. There is not a limitation however in specifying how many of each of those machines a process may have. In other words, for a process consisting of a number of machines:

Machine	Qty
Machine 1	q_1
Machine 2	q_2
.	
Machine N	q_N

N must be no greater than 50, and q_N simply must be nonnegative. Should there be a need that N to be larger than 50 for either the primary or auxiliary processes, please contact the developer.

5.3.2. Filtering

The automated filtering operation of the front end process generation is intended for fairly simple parts. Parts with multiple features are easily accommodated and machines in the primary machine database capable of achieving each of the specified part feature designs (i.e., dimensions and tolerances) are returned. However, for parts with more than one design of any feature type (e.g., a part with multiple holes, each with a different diameter, depth, and tolerances) the current coding will only consider the last entry of a feature type design in determining ‘passing’ primary machines. For example, for a part with two slots with unique and different designs, the tool will only consider the last of the slot feature designs inputted.

It is recommended that for parts with more than one unique design of a feature type, and not simply duplicates of the same feature, that each individual feature instance be inputted to determine the primary machines in the database capable of achieving the given feature design. The desired primary machines should be noted and the process generated by selecting them from a listing of all primary machines.

Not included in the filtering of production machinery is the material of the designed part. Machines in the database are assumed to be capable of operating on the fixed workpiece material. Where the use of specific materials for parts or components is standardized, or the machines in the database are flexible to work on different workpiece materials, this assumption is not a limitation. For the use of novel or new materials, machine capability in regards to material compatibility is left to the user of the Predictor tool in the process generation step of the front end.

5.3.3. Modeling Manufacturing Processes

The Predictor tool does not specify the order in which manufacturing processes should be carried out. For the purposes of performance estimations by the tool, the machines selected and / or required to achieve a specific part design are simply 'pooled', typical individual cost and environmental performances estimated, and then aggregated. Additionally, the internal workings and mechanics of individual machine operations (e.g., depths of cuts, feed rates, over-travel, fixturing, tool paths, internal automation, etc.) are not included; detailed workings are abstracted into a machine-level processing time. Modeling is conducted at this machine level of abstraction; the inside of a machine unit may be considered as a 'black box', where the items of concern and interest are solely the masses and energies flowing into and out of the machine, and the financial costs of the machine operation, all attributed per unit of production.

If there is more than one of the same machine on a production line, used in different operation steps to create different features, it is assumed that the machines have the same performances. Additionally, batch sizes and processing times are assumed to be the same, regardless of the specifics related to the individual operations. That is, the individual performances of multiples of the same machine creating multiple different features can not be differentiated from each other. For example, say a particular milling machine is used in two instances in the production of a part to create two unique slot feature designs. The contribution of that milling machine to the overall cost and environmental performance of the production line is the same for the two features created, regardless how different the feature creation operations may be. This limitation is due to the Excel coding whereby only one instance of a production machine is created for a proposed process. In high volume manufacturing environments, the use of highly specialized machinery to create each feature of a part may make this situation a somewhat rare occurrence.

Also, for machines with the capability or flexibility to create different part features in a single operation (e.g., by having multiple tools, automatically changing cutters, etc.), the effect on processing time must be manually captured, and may not necessarily be the same processing time recorded in the primary machine database as typical.

5.3.4. Sensitivity Analyses

After performing a Monte Carlo simulation with @RISK to understand the uncertainty in performance estimates, and thus the risks associated with making decisions supported by these estimates, it is helpful to also conduct a sensitivity analysis of the estimates, also easily accomplished using @RISK. However, the significant inputs to the estimate calculations given by the @RISK sensitivity analysis are ONLY those with input distributions. That is, *only* the significance of uncertain input parameters, which are modeled and named with @RISK input functions, is measured. The significance of known, or deterministic input parameters, which are not typically modeled with @RISK input functions, is not measured. When interpreting sensitivity analysis results, the absence of deterministic inputs into the estimate calculations must be considered. Other sensitivity analyses may be employed to gain a more complete picture of significant inputs. Alternatively, all inputs throughout the tool may be modeled with @RISK input functions; deterministic inputs may be modeled as uniform distributions, with equivalent lower and upper bounds, equal to the parameter value.

5.3.5. Databases

The outputs from the tool are only as good as the inputs to the tool; the saying, "garbage in = garbage out" certainly applies here. Effort and care should be taken in populating the databases with accurate information, and the numbers of machines, processing times, batch sizes, and hourly production rates (where applicable) also need to be as accurate as possible to ensure that model results reflect reality. Additionally, separate databases should be created to house the typical machine characteristics associated with creating different kinds of parts.

Populating these databases however requires some degree of historical information about machine operations. For established manufacturers with fairly standardized processes and machine selections, this requirement should not pose a substantial problem. Where no precedent exists such as for new or original part designs or new manufacturing technology implementation, best guess information on machine operations will have to suffice.

5.3.6. Decision Making

The feedback manufacturing cost and environmental information generated by the tool may be fed into existing decision processes as criteria for making decisions related to product design. The weighting of preferences for the cost and environmental performance criteria with respect to other design goals and requirements is left to designer(s), management, and / or company policies, and is not prescribed here.

Bottom line though, **the tool will not make decisions for the user.**

5.4. Interpreting Outputs from the Tool

In Figure 55 below, a screen shot of the Summary Outputs sheet is given for an example, hypothetical process. In this sheet the user:

1. Finds the aggregate results for the proposed primary and auxiliary manufacturing process performance.
2. Finds the high level breakdown of environmental impacts and financial costs into main categories.
3. Finds the percentage breakdown of results by machine type; that is, by primary and auxiliary machinery.

This sheet, as the name implies, is the main source for results information, at the highest level. The sources of the information in this sheet are the individual sheets for Environmental Inventory, Environmental Impacts, and Financial Costs. Looking to those sheets will provide more disaggregated results and a greater extent of lower level details. The sources of the information in those sheets are the per machine calculations found in the sheets where primary and auxiliary processes are calculated, and is the most disaggregated, providing the greatest level of detail.

		Primary	Auxiliary	Total	units
Main	Environmental SPS	291.101	76.863	367.965	mpt / part
	Financial Cost	3.556	0.702	4.258	$ / part
Inventory	Water Use	0.044	0.117	0.162	gal / part
	Landfill Waste	0.082	0.126	0.208	lb / part
	Recyclable Material	0.158	0.000	0.158	lb / part
	Special Waste	0.078	0.131	0.209	lb / part
	Energy	9.329	2.420	11.749	kWh / part
	CO2	12.464	3.233	15.697	lb / part

Breaking down Outputs by Machine Type:

		Primary	Auxiliary
Main	Environmental SPS	79.1%	20.9%
	Financial Cost	83.5%	16.5%
Inventory	Water Use	27.5%	72.5%
	Landfill Waste	39.4%	60.6%
	Recyclable Material	100.0%	0.0%
	Special Waste	37.3%	62.7%
	Energy	79.4%	20.6%
	CO2	79.4%	20.6%

Machines in Proposed Process

Primary	Auxiliary
Drill Press A	Coolant System A
Milling Machine A	Material Handling A
Washer A	Mist Collector A

Breaking down Main Outputs by Categories:

		Primary	Auxiliary	Total	units
Env	Utilities	239.461	62.121	301.582	mpt / part
	By-products	51.640	14.742	66.383	mpt / part
Costs	Utilities	0.876	0.221	1.097	$ / part
	By-products	-0.015	0.007	-0.008	$ / part
	Other / Traditional	1.255	0.474	1.729	$ / part
	Labor	1.440	0.000	1.440	$ / part

		Primary	Auxiliary
Env	Utilities	79.4%	20.6%
	By-products	77.8%	22.2%
Costs	Utilities	79.9%	20.1%
	By-products	195.7%	-95.7%
	Traditional	72.6%	27.4%
	Labor	100.0%	0.0%

Figure 55 Screen Shot of Summary Outputs

5.4.1 Developing and Using Estimate Statistics

The Excel tool analysis is deterministic and returns single point results. The uncertainty in the inputs and thus the outputs is not captured. These single point results are calculated from the mean, expected values of the inputs. Performing a simulation with @RISK will develop the statistics necessary to determine statistical confidence in results.

For example, total energy may be used as an output of interest to illustrate the difference between single point (deterministic) results versus the probabilistic results from a Monte Carlo simulation performed with @RISK. Using the Predictor tool for a proposed, hypothetical process the total energy is estimated to be 11.7 kWh / part, highlighted in Figure 55. Performing a Monte Carlo simulation, a histogram for the total energy is developed and shown in Figure 56.

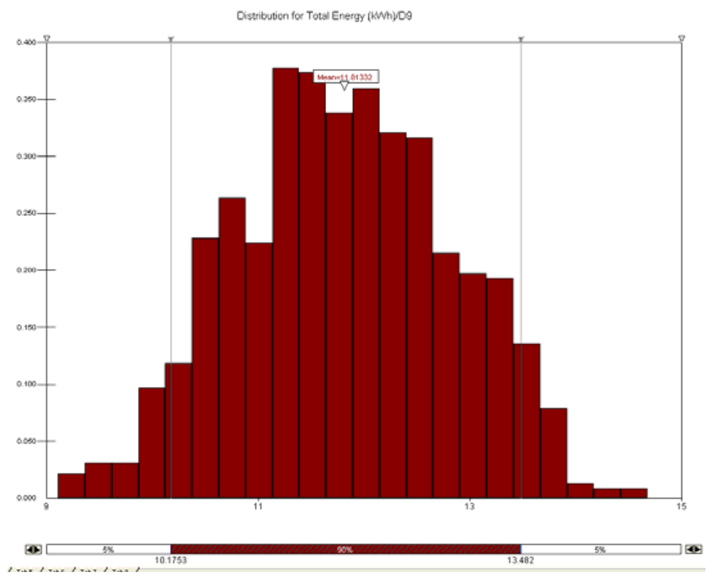


Figure 56 Histogram for Total Energy for Proposed, Hypothetical Process

The simulation iterated 900 times, and the mean and standard deviation of the assumed normal distribution are 11.8 kWh / part and 1.02 kWh / part, respectively. The mean of the distribution is very close to the Predictor tool single point result (of 11.7 kWh / part), but the Excel-based Predictor tool results lack any information on the spread or uncertainty of the result. This spread information is very important towards understanding the risks involved with making decisions supported by these results. The decision maker may now know the probability that the result of interest will fall within some range. For results with a range wider than acceptable, further information should be gathered to reduce the uncertainty of the inputs where possible and most impactful.

When making comparisons, the knowledge of the spread of the two values being compared is very important in order to ascertain the statistical significance of any potential difference. For example, say two hypothetical manufacturing processes A and B have total energies of 12 kWh / part and 11 kWh / part, respectively. It appears that B is preferable to A in terms of energy use; however, one cannot simply state that the total energies for processes A and B are significantly different. Using statistical inferencing techniques of either $(1-\alpha)100\%$ confidence intervals or hypothesis testing one may test whether the total energy of process B is indeed less than that of A, or that the total energies for both processes are not significantly different. The statistics developed from Monte Carlo simulations for both processes may be used to perform statistical inferences.

For model inputs with relatively little uncertainty the output distributions may be expected as very peaked with a narrow spread indicating low probability of results lying far from the mean result. In other words, as input uncertainty goes to zero the output results will approach deterministic results. However, this only addresses epistemic uncertainty related to imprecise knowledge of inputs, and not the aleatory uncertainty related to the variable and stochastic behavior of inputs, which is prevalent in manufacturing processes.

5.4.2 Scalar and Vector Indicators

Indicator outputs from the tool come in the form of aggregated scalars and disaggregated vectors. The aggregated scalars are the total financial costs in dollars and the total environmental impact in millipoints, and contain the summed amounts across primary and auxiliary machines and across categories. The disaggregated vector is the inventory environmental burdens, where each entry in the vector is a unique entity with its own units of measure. The aggregated scalars are high level indicators of the proposed manufacturing process's cost and environmental performances. The vector is a lower level indicator of the manufacturing performance in the sense that it contains more 'raw' detail of the actual manufacturing operation. The levels of detail afforded by these different indicators will be useful to decision makers at different levels in an organization with their own goals and objectives they are attempting to achieve.

Environmental and cost performances are aggregated for the proposed manufacturing processes. However, the costs and environmental burdens associated with particular part feature designs may be determined via the production machinery required to produce those features. In this manner, the additional 'costs', and degraded manufacturing performance, of additional part features may be estimated.

5.4.3. A Note on Environmental Impacts

The environmental inventory will be of interest to users of the tool because it contains information in units of measure that are more understandable versus an environmental impact score with its units of millipoints. Additionally, a manufacturing facility may have goals or requirements that certain burdens be less than some target values; raw environmental burden units are easier to measure, indisputable, and universal. The assignment of environmental impacts in millipoints, while useful in measuring life cycle environmental effects, has weaknesses. Primarily due to the contentiousness of eco-indicator values and the assumptions underlying their calculation, the acceptance of an environmental impact score as a stand alone indicator is still a ways off. Conducting Life Cycle Assessments/Analyses is still an open area of research that has made strides in helping people understand and consider life cycle impacts, but still has open issues and questions. The chief benefit is to provide a quick measure of feedback on the life cycle environmental performance of the items involved in the proposed manufacturing process. It is especially helpful for quick comparisons between potential alternatives.

5.5. Thesis Roadmap

In this chapter the instantiation of the proposed method as an Excel-based tool, including an overview, discussion on limitations, and a guide to interpreting results, has been presented. With the proposed method and the means to carry out the method established, it is time to turn attention to example problems in Chapters 6 and 7 and attempt to establish the Empirical Performance Validity, Theoretical Performance Validity, and thus Theoretical Structural Validity.

CHAPTER 6

ILLUSTRATIVE EXAMPLES

In this chapter two illustrative examples are presented to exercise the method proposed in this thesis, and the developed Excel-based tool, in a predictive fashion. The cost and environmental performances of the manufacture of two simple part designs is estimated using the method. The primary and auxiliary production machinery available in the databases to produce these simple parts, and their operating characteristics, are as realistic as possible, albeit hypothetical; thus caution is warranted in any attempts to draw conclusions from manufacturing performance estimates made in this chapter. The purpose of these examples is to exercise the tool and demonstrate the operation of both front end process generation and back end process accounting, and the possible design decision support available given populated machine databases. In Chapter 7 real manufacturing machinery data will be employed to estimate and assess the manufacturing performances of two automotive transmission gears, but the process planning aspects of the method are not examined given the prior installation of the pinion gear manufacturing processes. Thus, the focus of the two examples of this Chapter will be on the process planning / generation steps the method. The first of the examples is a simple part, called ‘A’ and a fairly simple production process with primary and auxiliary machinery not shared between other production lines. The second example is still a simple part design, called ‘B’, though somewhat more complex than the first and the manufacturing process is first examined in isolation from other production lines, then sharing of auxiliary machinery between the production of parts A and B is examined.

6.1 A Simple Part and Process

A hypothetical example is presented here as a proof of concept and utility of the developed method. A high volume product requires the simple part, called ‘A’, shown in Figure 57 as a key component; its material is generic steel. In addition to precisely meeting design dimensions, the part must be clean to be successfully integrated into the next level assembly; the cleanliness requirement is met by adding a final washing step to the production process.

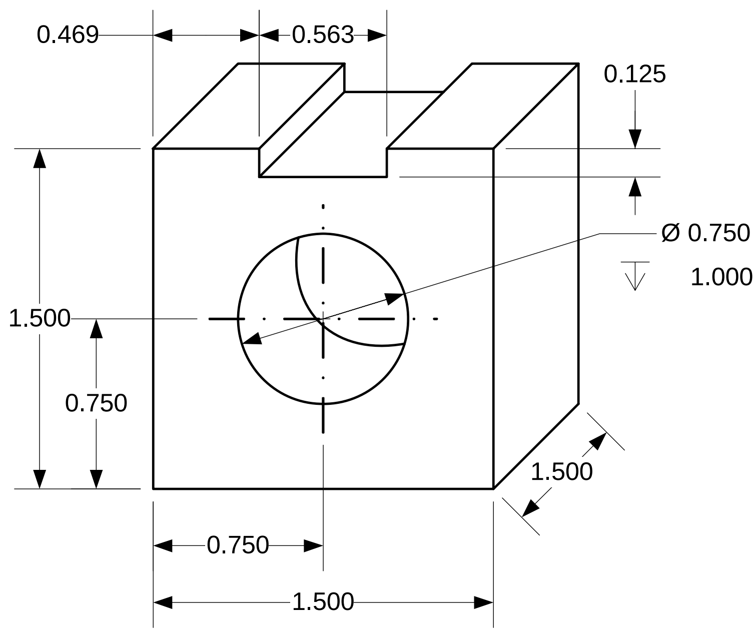


Figure 57 Part A Dimensioned Drawing

. The part feature designs in Figure 57 are inputted to the front end of the tool / method, on the left hand side of Figure 12 back in Chapter 3. The specific part features of part A are a hole, with a depth and a diameter, and a slot, with a width and a depth. The feature designs with their dimensions and dimensional tolerances are given in Table 4; these items will be used in the filtering of the available primary machinery in the process generation step. It is assumed that the tolerance level on the feature dimensions is not known yet (i.e., it has yet to be specified), but will be greater than 0.001in.

Table 4 Part A Feature Designs

Feature	Dimension (in.)	Tolerance (in.)
Hole Diameter	0.750	>0.001
Hole Depth	1.000	>0.001
Slot Width	0.563	>0.001
Slot Depth	0.125	>0.001

6.1.1. Process Planning for Part A

For the front end process generation step of Figure 12, a process is manually selected from all possible means of creating the desired features, and proposed for manufacturing this part from machined blocks of steel supplied by a vendor. The major dimensions of the blocks are to be held within the allowed tolerances of ±0.005in. by the supplier, and they do so with a very high rate of success. The major processing steps required are milling the slot, drilling the hole, and washing the finished parts; the actual processing order is unknown and it is entirely possible that the hole be drilled before the slot milled. To support this automated high-volume process, coolant systems and mist collectors are required on both the milling machine and the drill press as auxiliary machines; this proposed, hypothetical process is laid out in Figure 58. The function of the auxiliary coolant system is to supply cutting fluid to the cutting operations, collect used coolant, and circulate used coolant through filters to clean the fluid for reuse by removing metal chips carried by the fluid. The mist collector removes cutting fluid mist generated by the cutting operation to prevent mist from reaching unwanted concentration levels within the facility environment. Additionally there are automated material handling machines, not pictured in Figure 58, which connect each primary process step, and are present at the beginning and end of the process.

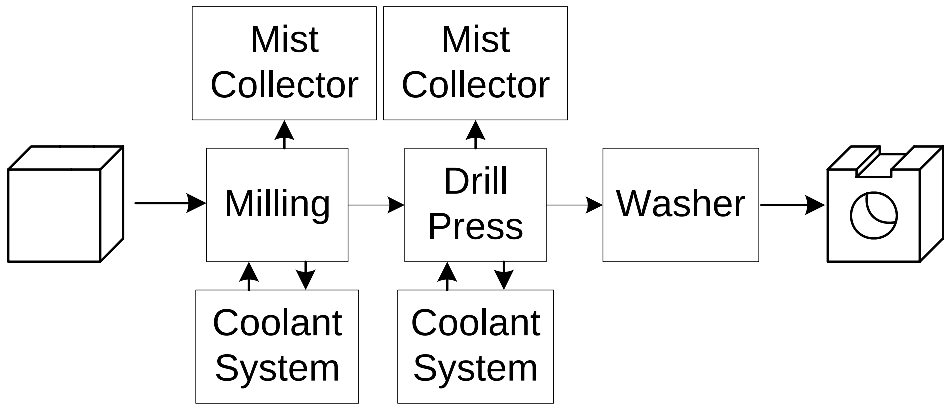


Figure 58 Proposed Process for Part A

Though the general processing method for producing part A has been manually selected, the particular machinery to be used must be determined. The Filtering operation of the developed tool will be employed to help guide machine selection. The operation of the filtering has already been described in Chapter 3, but essentially multiple if…then loops are implemented to filter out those available primary process machines which are incapable of achieving the inputted feature designs (i.e., feature dimensions and dimensional tolerances) at the required production volume. Examples of machine process capabilities, taken from the primary database for this illustrative example are given below in Figure 59. The machines and their process capabilities are hypothetical and not related to manufacturing machinery which may exist in reality. For each machine the features created are listed, and the bounds on the dimensional capability of the machine for those features, and the lower limit of tolerance on each dimension are given. Additionally, the maximum hourly production rate is listed.

Machine	Features Created	DL	DU	TL	MHP	Reqd Aux Machinery
Drill Press A	hole diameter	0.1	2	0.001	150	Coolant System A
	hole depth	0	2.5	0.001		Material Handling A
						Mist Collector A
Drill Press B	hole diameter	0.05	1	0.005	125	Coolant System B
	hole depth	0	2	0.005		Material Handling B
						Mist Collector B
Drill Press C	hole diameter	0.05	3	0.001	50	Coolant System C
	hole depth	0	2	0.001		Material Handling C
						Mist Collector C
Drill Press E	hole diameter	0.5	5	0.01	250	Coolant System A
	hole depth	0	4	0.01		Material Handling A
						Mist Collector A
Milling Machine A	slot width	0.1	2	0.001	200	Coolant System A
	slot depth	0	0.5	0.001		Material Handling A
						Mist Collector A
Milling Machine B	slot width	0.05	2.5	0.005	150	Coolant System B
	slot depth	0	1	0.005		Material Handling B
						Mist Collector B
Milling Machine C	slot width	0.1	3	0.001	65	Coolant System C
	slot depth	0	0.25	0.001		Material Handling C
						Mist Collector C
Milling Machine D	slot width	0.25	5	0.01	250	Coolant System D
	slot depth	0	0.75	0.01		Material Handling D
						Mist Collector D
Washer A	--				125	Material Handling A
Washer B	--				90	Material Handling B
Washer C	--				75	Material Handling C
Washer D	--				200	Material Handling D

Figure 59 Example Process Capabilities from Primary Machine Database

In Figure 59, DL is the lower bound on dimensional capability for a particular feature and DU is the upper bound, in units of in.; TL is the tolerance limit for a dimension of a feature, in units of in. as well, and MHP is the maximum hourly production rate of the machine. In addition to the feature designs of part A given in Table 4 above, it is known that nominally there are 200,000 of part A required in a year. With the assumptions for working hours per day, week, and year, discussed later, it is determined that the hourly production rate of part A must be at least 104, assuming evenly distributed production throughout the year and not considering quality affects such as scrapped or defective parts. It is seen in Figure 59 that dimensional and tolerance capabilities are given for drill presses and milling machines, but not the part washers. The part washers are considered as primary machinery due to their direct interaction with the units of production, but they do not directly create or affect the feature designs of the part. These part washers, and other primary machinery which do not directly create or affect part feature designs, are not included in the Filtering operations, and must be added to the primary process manually. The maximum hourly production rate of the washers must be considered as a decision rule, given the known required hourly production rate of the part of interest, for selected an appropriate washer for the process.

In Table 4 above, the tolerances on the feature designs are not explicitly set, though they may be no smaller than 0.001 in. The setting of the feature tolerances will strongly influence both the selection of the production machinery and the operation of that machinery. In Figure 60, the effect of varying the tolerance level on the feature designs on the selection of primary production machinery is given. For each tolerance level or range, the primary machines (i.e., drill presses and milling machines) which successfully meet all of the selection criteria of dimensional capability, tolerance capability, and production volume capability ‘pass’ and are listed. For the hypothetical machines available and given in the primary machine database, as the tolerance level reduced, and tolerances became tighter, fewer and fewer primary production machines 'pass' all of the selection criteria. From the list of passing primary machinery for a given tolerance level on the feature designs, the desired machines must be manually selected.

Tolerance (in.)	>0.01	0.009 - 0.005	0.004 - 0.001
Passing Machines:	Drill Press A	Drill Press A	Drill Press A
	Drill Press B	Drill Press B	Drill Press F
	Drill Press E	Drill Press F	Milling Machine A
	Drill Press F	Milling Machine A	
	Milling Machine A	Milling Machine B	
	Milling Machine B	Milling Machine E	
	Milling Machine D	Milling Machine H	
	Milling Machine E		
	Milling Machine H		

Figure 60 Passing Primary Machinery for Tolerance Ranges on Features of Part A

In this situation, the tolerances set on the part features (i.e., the hole and slot) were set equivalently, but this does not have to be the case. For example, the slot feature control dimensions of width and depth could have tolerances set to 0.01in., and the hole feature control dimensions of depth and diameter could have been set differently, say to 0.001in., and the Filtering operation successfully employed. Tolerances were set equivalently to the feature dimensions for ease of illustrating the effect of tightening tolerances on machine selection. The effect of changing tolerance requirements on machine selection is clear, and has a straightforward impact on the Filtering operation. The effect of changing the tolerance requirements on machine operation is not as simple, and is not automated in the Excel-based tool; in other words; the effect of a different tolerance specification on machine operation must be manually considered and implemented in the tool. This is done via an abstraction of machine operation specifics to processing time; knowledge of the processing time – feature tolerance relationship is key towards including this important aspect of quantifiably connecting machine operation, and thus performance, as a function of feature tolerance.

The primary machines which do not directly create or affect the part feature designs, but play an important role in the production process, the part washers, must be added to the primary production process. The simplified selection criterion for choosing a washer the ability to meet the required production rates for the part of interest. Given the required hourly production rate of part A is known to be 104, the available part washers in the primary database, also shown in Figure 59, are manually filtered and passing machines given in Figure 61.

Passing Washers
A
D
E

Figure 61 Passing Washers for Part A Process

With the passing primary production machinery determined, the auxiliary process to potentially support those primary machines needs to be determined. There are two methods for assembling the auxiliary process: (1) manually select the desired auxiliary machines from the listing of all available auxiliary machines, perhaps guided by previous experiences or company standards or best practices; and (2) generating the auxiliary process automatically using the auxiliary machinery specified for machinery in the primary machine database, shown in Figure 59. A listing of all of the available auxiliary machinery is given in Figure 62; determining which of the auxiliary machinery from this list requires knowledge of the capabilities of the various auxiliary machines to support particular primary machine operations successfully.

Available Auxiliary Machines
Coolant System A
Coolant System B
Coolant System C
Coolant System D
Material Handling A
Material Handling B
Material Handling C
Material Handling D
Mist Collector A
Mist Collector B
Mist Collector C
Mist Collector D

Figure 62 Available Auxiliary Machines

Alternatively, specific auxiliary machinery may be specified to support primary machines. In reality, there will most likely not be as many options for auxiliary machinery and auxiliary machines are likely able to support similar production operations carried out by primary machinery from a number of manufacturers. The various types of auxiliary machines listed in Figure 62 do not necessarily need to be wholly different machines offered by competing manufacturers; they may be machine model variations with differing capabilities. For example, for collectors there are likely to be different size collectors depending on the number of primary machines to be supported, and the amount of material to be collected. Generating the auxiliary process automatically, using the specified auxiliary machines given for selected primary machines, potential process machinery combinations are given in Figure 63.

Selected Primary Machine	Required Auxiliary Machines
Drill Press A	Coolant System A Material Handling A Mist Collector A
Milling Machine A	Coolant System A Material Handling A Mist Collector A
Washer A or E	Material Handling A

Selected Primary Machine	Required Auxiliary Machines
Drill Press A	Coolant System A Material Handling A Mist Collector A
Milling Machine A	Coolant System A Material Handling A Mist Collector A
Washer D	Material Handling D

Selected Primary Machine	Required Auxiliary Machines
Drill Press F	Coolant System B Material Handling B Mist Collector B
Milling Machine A	Coolant System A Material Handling A Mist Collector A
Washer A or E	Material Handling A

Selected Primary Machine	Required Auxiliary Machines
Drill Press F	Coolant System B Material Handling B Mist Collector B
Milling Machine A	Coolant System A Material Handling A Mist Collector A
Washer D	Material Handling D

Figure 63 Potential Process Machinery Combinations

For a selection of primary machines to compose the primary process to produce part A, the necessary auxiliary machinery is given in Figure 63. It has been assumed that feature tolerances in the range of 0.004 in. to 0.001 in. have been chosen, and thus the available passing primary machines for this part design are Drill Press A and F, Milling Machine A, and Washers A, D, and E. When process planners are faced with a machine selection decision such as this one, given equally viable options for successfully producing the part of interest, choosing one machine over another is primarily a business decision. Previous experiences with the machine vendor, service and support received, previous issues, ease of maintenance, production history, and costs all factor into the decision. With the use of the tool developed in this thesis the inclusion of estimated environmental performance of production machinery into machine selection decision criteria may be accomplished. With no explicit preference for which machines to select for the primary and auxiliary processes to produce part A, machines arbitrarily chosen for the manufacturing process depicted in Figure 58 are given in Figure 64.

Primary Machines	Auxiliary Machines
Drill Press A	Coolant System A
Milling Machine A	Material Handling A
Washer A	Mist Collector A

Figure 64 Selected Machines to Produce Part A

With the process to produce part A generated, this process may now be accounted in the back end.

6.1.2 Assumptions and Inputs

A number of assumptions were made in the back end steps of Figure 12 to create an inventory of environmental burdens, and estimate the costs and environmental impacts for the process proposed to manufacture the hypothetical part.

- The waste stream of by-products is made up of landfillable wastes, recyclable materials, and special, or hazardous, wastes that require alternative disposal methods; within each waste stream category, the content is homogeneous;
- Metal chips removed from parts are wholly recyclable;
- Assuming the worst case uncertainty, input parameters with uncertainty are assigned a uniform distribution about their expected nominal value;

- Auxiliary equipment is not shared by other production lines; only production of the example part is supported; sharing the auxiliary machinery between multiple production lines would reduce per piece impacts associated with that machinery.
- The production line is up and running; that is, in steady state operation. Start up, shut down, and preventive maintenance procedures are not included, but their impacts on costs and the environment could be significant (e.g., flushing of fluids from washers and coolant systems, or turning on a heat treat furnace).
- Cost and environmental performances are attributed to individual manufactured parts (i.e., per piece) in the context of providing decision support to the designers of those parts. For more on efforts to model environmental burdens, particularly for washers, please see (Román, et al. 2006).

In addition to the uncertainty associated with the characteristics of individual machines in the machine database, there is assumed uncertainty associated with operating cost rates in the cost database and a couple of facility parameters: number of operators, yearly production rate, and the time to depreciate capital expenses. Lower and upper bounds on these uncertain inputs are shown below in Table 5.

Table 5 Cost and Facility Parameters with Uncertainty

Costs	LB	UB	Units
Operator Labor	40.00	60.00	$/hr
Electrical Energy	0.020	0.060	$/kWh
Compressed Air	0.010	0.030	$/cf
Water	0.00150	0.00331	$/gal
Regular Landfilling	25.00	50.00	$/ton
Recycling	-300.00	-200.00	$/ton
Special Wastes	65.00	90.00	$/ton
Facility Parameters	**LB**	**UB**	**Units**
No. Operators	2	4	people
Yearly Production	150000	250000	units
Years to Depreciate	3	10	years

Other input parameters have essentially no degree of uncertainty. These deterministic input parameters for Eco-indicator 99 values, from Sima Pro LCA software (2005), used in the conversion step of Figure 12 and stored in a database, and other facility parameters are given below in Table 6.

Table 6 Deterministic Input Parameters

Eco-indicator 99	Value	Units
Electricity	25.668	mpt / kWh
Compressed Air	25.668	mpt / kWh
Water	0.001	mpt / gal
Landfilling	1.397	mpt / lb
Recycling	-21.727	mpt / lb
Special Wastes	2.794	mpt / lb
CO2	8784.029	mpt / ton

Facility Parameters	Value
Shifts / Week	5
Hours / Day	8
Days / Week	5
Weeks / Year	48

For the landfill, recycling, and special, or hazardous, by-product streams, the exact constitution of those streams needs to be known in order to properly ascribe an

Eco-Indicator 99 value to it. Assumptions made in determining the Eco-Indicator 99 values in Table 6 that are not obvious are as follows:

- Electricity is for the typical US grid composition, shown in Table 7 (EPA 2006);

Table 7 Typical US Grid Composition

Fuel	Average Percentage
Coal	52%
Nuclear	20%
Natural Gas	16%
Hydro	7%
Other*	5%

*Nonhydro renewables and oil, not included in the model

- The impact for compressed air is attributed solely to the electricity required to generate it;
- 'General' trash is the waste stream sent to landfill;
- Steel removed in cutting operations as chips is the only material recycled;
- Without knowing exact constitution, the waste stream of special wastes is assumed to be twice as 'bad' as the general trash sent to landfill.
- Water is assumed to be overwhelmingly benign and thus given a very low eco-indicator value. However, this assumed value does not necessarily capture the life cycle environmental impacts associated with water treatment, collection, and supply; in other words, the man-made water infrastructure system.

The characteristics of the primary and auxiliary machinery are stored in the machine databases. The hypothetical values stored in the database for each of the machines in the proposed process are shown in Tables 8 and 9 for primary and auxiliary machinery, respectively. Assuming little information is known beyond a range within which all values are equally likely, uncertain inputs are assigned a uniform distribution and lower and upper bounds are presented. If empirical data of machine variability exists though, some other probability density function may be assigned to inputs.

Table 8 Assumed Primary Machinery Database

		CNC Milling A		Drill Press A		Washer A	
Characteristic	**Units**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**
Electrical Power	kW	2.5	7.5	7.5	12.5	11	19
Compressed Air	cfm	7.5	12.5	4	6	95	105
Water Use	gph	0		0		6	10
Landfillable Waste	lb / hr	2	4	1	3	3	7
Recyclable Material	lb / hr	3	4.5	12	14	0.2	0.8
Special Waste	lb / hr	1	3	3.5	6.5	0.5	3.5
Batch Size	--	1		1		15	
Processing Time	min	0.5	1	0.4	0.6	4	6
Yearly Tooling	$	42000	58000	12000	18000	2500	7500
Yearly Consumables	$	22000	28000	8500	12000	12000	18000
Acquisition	$	250000		100000		500000	

Table 9 Assumed Auxiliary Machinery Database

		Mist Collector A		Coolant System A		Material Handling A	
Characteristic	**Units**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**
Electrical Power	kW	7.5	12.5	2	5	4	7
Compressed Air	cfm	3	7	9	11	1	6
Water Use	gph	0		8	15	0.4	1
Landfillable Waste	lb / hr	1	4	5	15	0.25	1
Recyclable Material	lb / hr	0		0		0	
Special Waste	lb / hr	2	6	8	10	0.25	1
Yearly Consumables	$	8500	15000	14000	26000	2000	2600
Acquisition	$	95000		250000		50000	

Since the production line for part A essentially exists in isolation and production machinery is not shared between other production lines, determining the number of production machines, and the auxiliary hourly production rates is a simple exercise. The number of machines may be determined simply by looking at Figure 58, and the hourly production rates of auxiliary machines by determining the hourly production rates of the primary machines supported by each machine. The number of machines in the process to produce part A, and the hourly production rates of the process are given in Tables 10 and 11, respectively.

Table 10 Machines in Process to Produce Part A

	Numbers of Machines	
Primary	Milling Machine	1
	Drill Press	1
	Washer	1
Aux	Mist Collector	2
	Coolant System	2
	Material Handling	4

Table 11 Hourly Production Rates

Hourly Production Rates	
Mist Collector	104
Coolant System	104
Material Handling	104
Production Line	104

6.1.3 Manufacturing Performance Estimates

Using the generated process, machine database inputs, numbers of machines, and the auxiliary production rates all under the stated assumptions, manufacturing performance estimates are generated. For this example the results of the uncertainty analysis are first given; the 'auto' setting in @RISK was used to determine the number of iterations to run, and results converged after about 1200 iterations. As illustrative of the results from the Monte Carlo simulation performed, a distribution of the environmental *SPS* is presented in Figure 65 with some of its descriptive statistics, and the sensitivities of the ten most significant uncertain inputs to the *SPS* in Table 12.

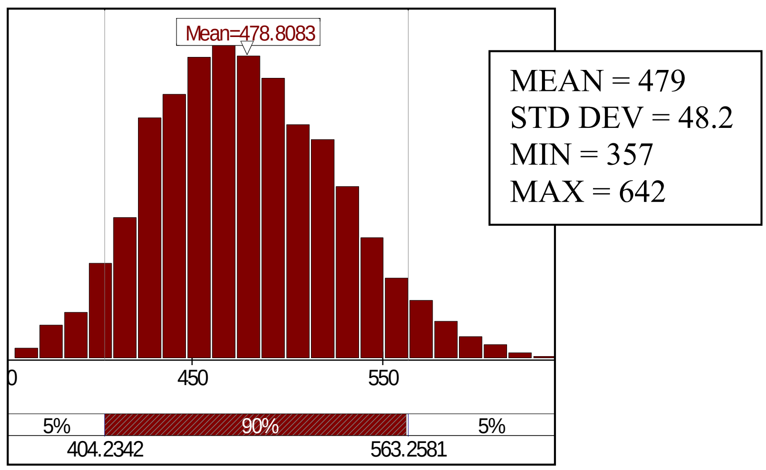


Figure 65 Distribution of Environmental SPS (millipoints)

Table 12 Sensitivities of Single Point Environmental. Score

Sensitivity		
Rank	**Name**	**Regr**
#1	Yearly Production of part	-0.574
#2	Washer A / Processing Time (min)	0.539
#3	Material Handling A / Compressed Air (cfm)	0.470
#4	Milling Machine A / Processing Time (min)	0.203
#5	Mist Collector A / Compressed Air (cfm)	0.184
#6	Milling Machine A / Compressed Air (cfm)	0.144
#7	Washer A / Compressed Air (cfm)	0.137
#8	Coolant System A / Compressed Air (cfm)	0.094
#9	Drill Press A / Compressed Air (cfm)	0.043
#10	Drill Press A / Processing Time (min)	0.039

The sensitivities are found using a regression analysis and identify those uncertain inputs which have the greatest effect on outputs (Palisade 2002). A positive or negative regression value is indicative of a positive or negative correlation of the input to the output, respectively; the greater the absolute regression value, the more significant the input. A distribution such as Figure 65 and the sensitivities as in Table 12 are available for all of the previously defined indicators of manufacturing performance. The normal distributions of the indicators of manufacturing performance are summarized in Table 13.

Table 13 Part A Manufacturing Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	479	48.3	357	642	mpt / part
Financial Cost	5.41	1.027	3.10	9.15	$ / part
Water Use	0.298	0.056	0.178	0.472	gal / part
Landfill Waste	0.35	0.075	0.19	0.60	lb / part
Recyclable Material	0.16	0.017	0.11	0.21	lb / part
Special Waste	0.36	0.051	0.24	0.52	lb / part
Energy	15.2	1.53	11.4	20.4	kWh / part
CO2	20.37	2.042	15.19	27.27	lb / part

Given the hypothetical nature of this example, these manufacturing performance estimates are thus hypothetical as well, and any conclusions made can only be limited in nature. The validation of these performance estimates is frankly not possible; however, the front end process generation of the tool has been exercised somewhat, and an example of the back end process accounting has been given.

6.1.3.1. A Parametric Study of Manufacturing Performances

The effect of part feature tolerance specifications on machine selection has been demonstrated in the previous section; the selection of manufacturing processes and machinery will strongly influence the cost and environmental performances of a part in its manufacture, but only partly. The other major component which determines manufacturing performance is the operation of the machinery in a production process which also strongly influenced by feature tolerance specifications. Similar to the parametric studies conducted in Chapter 3 to understand the behavior of the environmental burden models as a function of feature tolerances, the manufacturing performance behavior of the process selected to produce part A as a function of the feature tolerances of part A will be examined here. The particular primary machines were selected because of their capability to achieve tolerances on the hole and slot features in the chosen range of 0.004in. to 0.001in. Milling Machine A and Drill Press A were selected from a narrowed list of passing primary machines capable of that level of tolerance range. Washer A and the auxiliary machines were further added manually to complete the assembly of the process proposed for producing part A. While the particular machines were selected based on the required feature tolerances of part A they are capable of producing similar parts with a range tolerance requirements. The dimensional and tolerance capabilities of the primary machines in the process to produce part A are given in Figure 66.

	Features Created	DL (in.)	DU (in.)	TL (in.)	Typical Tolerance (in.)	TU (in.)
Drill Press A	hole diameter	0.100	2.000	0.001	0.025	0.050
	hole depth	0.000	2.500			
Milling Machine A	slot width	0.100	2.000	0.001	0.025	0.050
	slot depth	0.000	0.500			

Figure 66 Dimensional and Tolerance Capabilities of Primary Machines for Part A

In Figure 66 the lower and upper bounds on feature dimensions (DL and DU), and the tolerance limit and upper bound (TL and TU) are given. The range of tolerance is of interest here since the major dimensions of the features of part A are fixed, but the tolerance level parameter will be varied. A typical tolerance level is also given in Figure 66; this tolerance is the midpoint between the limit and upper bound of tolerance and assumed to be the tolerance achieved when machine processing time is typical. The process capabilities of the two primary machines in Figure 66 have been simplified somewhat; the tolerances on the dimensions which define the feature created have their tolerances set jointly. While it may be expected that these dimensions are not wholly independent of each other in their designs and manufacturability, it is easy to imagine a situation where different tolerances may be required on dimensions for the same feature.

Considering the hole feature created by Drill Press A; if part A were assembled to a precise shaft, but the shaft did not bottom out when assembled to part A, it is clear that the tolerance on the diameter of the hole is much more important than the depth of that hole. The tolerance on the diameter would most likely be set considerably tighter than the hole depth, because the part design does not wish to specify tight feature tolerance unnecessarily and incur greater manufacturing expense than necessary.

In the previous estimates of manufacturing performance an implicit assumption was made whereby processing time is constant as a function of feature tolerance level. The typical processing time for the primary machines was used in computing the manufacturing performance estimate regardless of the part feature tolerance designs. This situation may occur in early product design, when a product designer simply wants to get quick feedback on the likely manufacturing performance of his or her part design.

In the earlier stages of product design (i.e., conceptual design) the process plan is likely wholly unknown and thus to predict manufacturing performances typical processing times of primary machines may be the best option for getting initial, ballpark manufacturing performance estimates.

In this study however, the effect of feature tolerance on processing times will be considered. The typical processing time associated with each primary machine which creates part features (i.e., the drill press and milling machine, but not the washer) will be correlated with the 'typical' machine tolerance capability, located in the middle of the tolerance capability range. Assuming a 2nd order relationship, the processing time at the tolerance limit will be twice that of the typical processing time, and the processing time at the upper bound for tolerance will be half the typical value. These processing times for the primary machines at the different feature tolerance levels are given in Table 14, and plotted in Figure 67.

Table 14 Primary Machine Processing Times at Different Feature Tolerance Levels

	Processing Time at TL (min)	Typical Processing Time (min)	Processing Time at TU (min)
Drill Press A	1.00	0.50	0.25
Milling Machine A	1.50	0.75	0.38

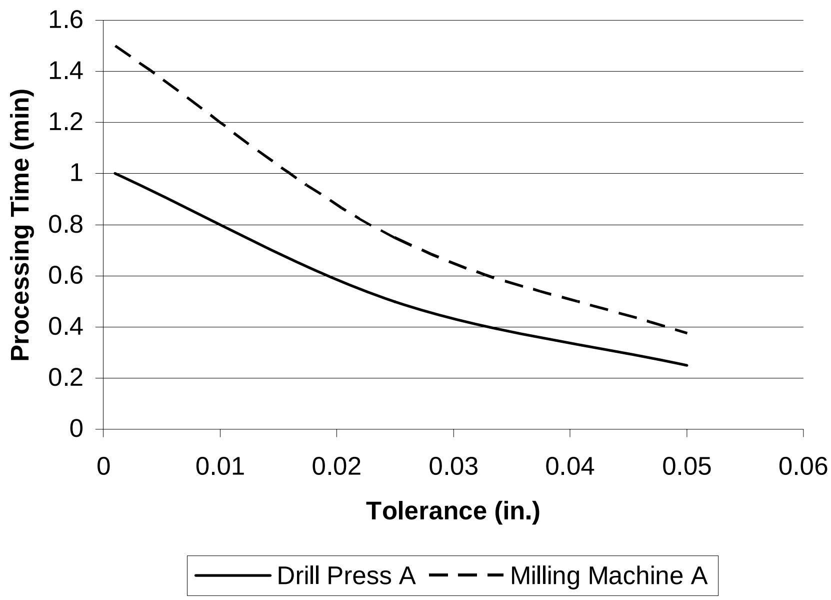


Figure 67 Processing Time as a Function of Feature Tolerance for Primary Machines to Produce Part A

These processing times as a function of each of the feature tolerance will be used to investigate the performance of the process selected to produce part A, measured by SPS, financial cost, and energy use, as a function of the tolerance specifications for the features of part A. In this study all other inputs to the performance estimation models will be held constant and only the processing times for the milling machine and drill press will be varied according the tolerances required on the features created by that machine. In other words, for changes in the feature tolerances for the hole and the slot the processing time of the drill press and the milling machine will be adjusted, respectively. In this study additional primary and auxiliary machinery to handle differing production volumes is not considered; if they were there would simply jump discontinuities in the manufacturing performances as a function of feature tolerance, at those tolerance levels where additional machinery is required. This behavior was discussed and presented in Chapter 3 and it is not necessary to show again.

Tolerance on the hole and slot features of part A are set at the tolerance limit, at the typical tolerance, and at the tolerance upper bound, both jointly and independently. Seven different scenarios for the feature tolerances were examined: the hole and slot tolerances are varied jointly, the hole feature tolerance is fixed at each tolerance level while the slot feature tolerance is varied, and the slot feature tolerance is fixed at each tolerance level while the hole feature tolerance is varied. For each part feature tolerance scenario the associated processing time of the appropriate primary machine is inputted in the back end process accounting section of the developed tool. The processing times inputted are those given in Table 14. The joint variation scenario is the setting of the hole and slot feature tolerances equivalently and varying from tolerance limit to tolerance upper bound together. The other scenarios involve fixing the tolerance specification for one feature while the tolerance of the other feature is varied from the tolerance limit to the tolerance upper bound. For example, the hole feature may be set at its tolerance limit, where the drill press has the maximum processing time. With the drill press set at its maximum processing time at the hole feature tolerance limit, the tolerance of the slot feature varied from the tolerance limit, to the typical tolerance, to the tolerance upper bound, and the processing time of the milling machine adjusted accordingly at each step. This scenario is labeled in the following Figures as ‘Drill at TL’. Looking at SPS, financial cost, and energy use as key indicators of manufacturing performance, and estimated using the deterministic outputs of the developed tool, these estimates for each of the seven feature tolerance scenarios, as a function of the feature tolerance being varied, are found in Figures 68, 69, and 70, respectively.

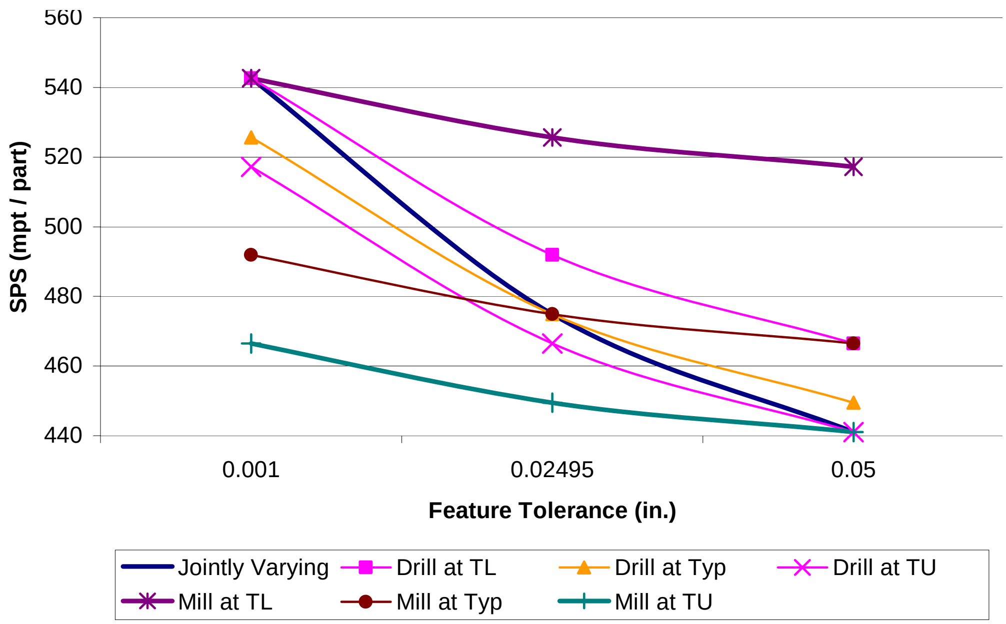


Figure 68 SPS of Manufacturing Process as a Function of Feature Tolerances

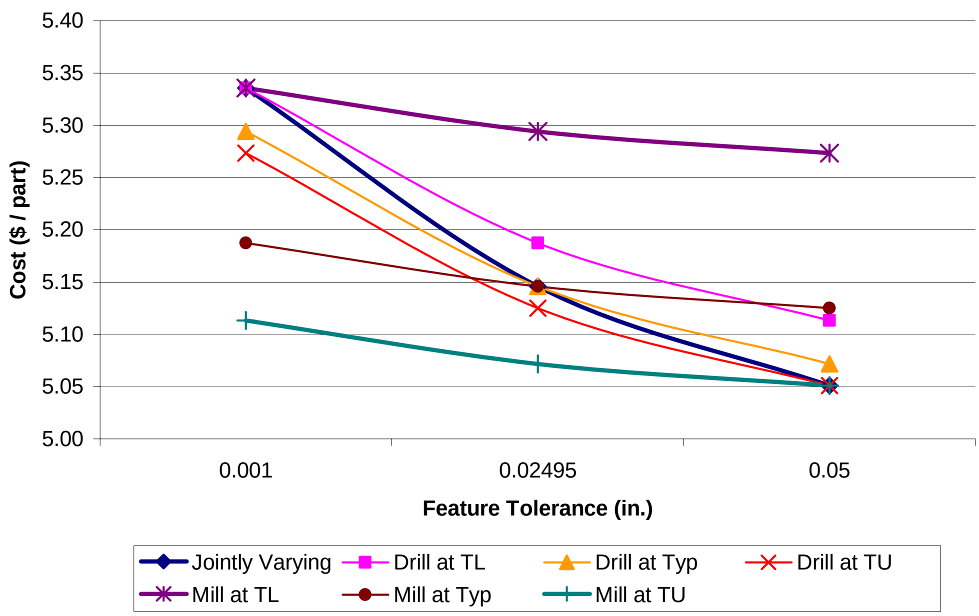


Figure 69 Cost of Manufacturing Process as a Function of Feature Tolerances

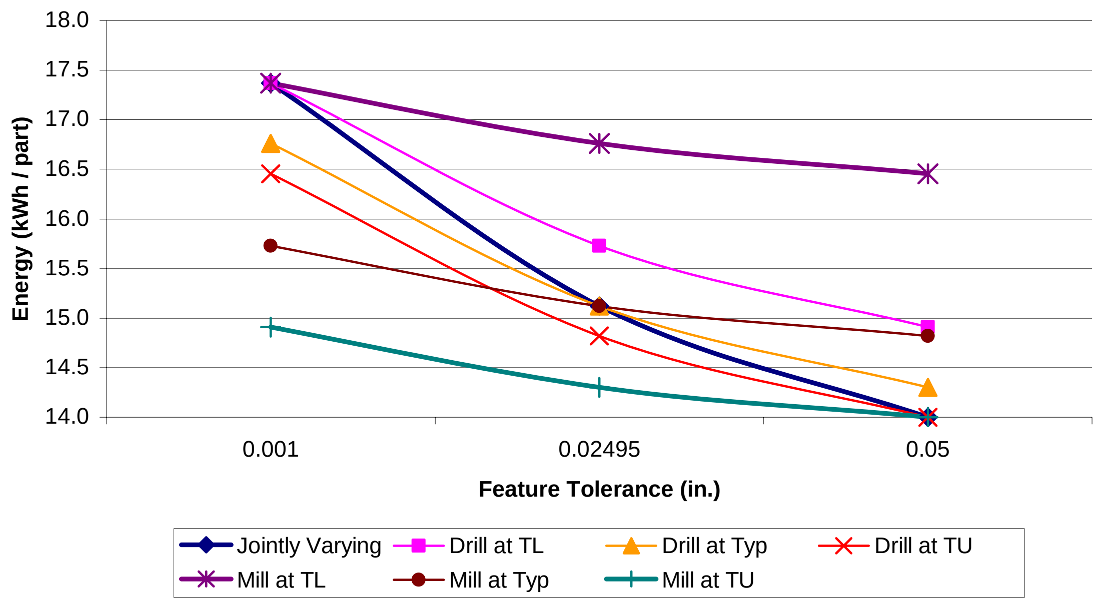


Figure 70 Energy Use of Manufacturing Process as a Function of Feature Tolerances

The shape of the plots contained in Figures 68, 69, and 70 are seen to be of the same form across the Figures, though the scales are different. This may be explained by the shapes of the processing time – feature tolerance curves for this study given in Figure 67; both primary machines' processing times are a 2nd order function of feature tolerance, though with slightly different curves and offsets. Explained in Chapter 3, the shape of the manufacturing performance curve as a function of feature tolerance is wholly dependent on the shape of the curve relating machine processing time to the feature tolerance. Also, the curves for the different scenarios in each of the three Figures above lie within an envelope defined by the limits of tolerance of the slot feature and the associated processing time setting of the milling machine; that is, the upper boundary of the envelope is 'Mill at TL' and 'Mill at TU'. All the other scenario curves exist within this envelope. This behavior may be explained by the summed processing times of both primary machines at each tolerance level. When the milling machine is at the tolerance limit, its processing time is 1.5 minutes; the processing times of the drill press over the range of tolerances, from the limit to the upper bound, are 1.0 minutes, 0.5 minutes, and 0.25 minutes. Summing these processing times at each tolerance level of the hole feature yields total part processing times of 2.5 minutes, 2.0 minutes, and 1.75 minutes for the tolerance limit, typical tolerance, and the upper bound of tolerance, respectively. No other tolerance scenario will have summed part processing times as *high* at the same tolerance level. At the upper bound of tolerance for the milling machine the processing time is 0.38 minutes and the drill press processing times are the same as just given. Summing these processing times at each tolerance level of the hole feature yields total part processing times of 1.38 minutes, 0.88 minutes, and 0.63 minutes for the tolerance limit, typical tolerance, and the upper bound of tolerance, respectively. Similarly, no other tolerance scenario will have summed part processing times as *low* at the same tolerance level. Given that processing time is the chief driver in estimating environmental burdens, for constant numbers of machines and environmental burden rates, and environmental burden rates are used as the basis for the SPS and factor into the costs, a maximum processing time should yield the highest (i.e., worst) estimates of manufacturing performance. The converse is equally true; a minimum processing time should yield the lowest (i.e., best) estimates of manufacturing performance.

In the example given in Section 6.1.1 all of the part feature tolerances are set to be in the range of 0.004in. to 0.001in. It is seen from the preceding Figures that the manufacturing performance estimates calculated initially should actually be higher, indicating worse manufacturing performance. Performance estimates should be higher because the typical processing times were used in the estimation models, irrespective of the feature tolerance requirements. However the tolerance range of 0.004in. to 0.001in. has the tolerance limit as its lower bound, and machine processing time will be at its maximum. Manufacturing performance is worst at the tolerance limit. If the features of part A all have their tolerances set to the tolerance limit of 0.001in., manufacturing performance estimates may be found by calculating using the processing time – feature tolerance relationship which provides the basis for the plots in Figures 68, 69, and 70. The deterministic performance estimates for SPS, financial cost, and energy use determined at the tolerance limit (maximum processing time) and also the typical tolerance (typical processing time) are given in Table 15. Percentage error is also given in Table 15 and measures the amount by which the performance estimates found using the implicit assumption of typical processing time regardless of feature tolerance level are off from the more accurate estimates found using the processing times at the tolerance limit.

Table 15 Difference in Performance Estimates at Tolerance Limit versus Typical Operation

Performance Indicator	TL	Typical	% Error
SPS (mpt / part)	540	475	12.0%
Cost ($ / part)	5.34	5.14	3.7%
Energy (kWh / part)	17.4	15.2	12.6%

In Table 15 it is seen that the percentage errors for the SPS and energy use performance indicators are significant. By using the assumption of 'flat' or constant processing time, these manufacturing performance estimates are both off from the more accurate, expected estimates found using processing time at the tolerance limit by about 12%. In a situation where the processing time – feature tolerance relationship is unknown, this is perhaps an acceptable outcome since initial performance estimates are at least arguably in the correct order of magnitude and ballpark of the actual performance estimates.

The performance estimate of financial cost is off by a nearly negligible amount; that is, using the less accurate typical processing times for ‘typical’ tolerances, rather than the more accurate processing times for the tolerance limits, does not greatly change the cost performance estimate. The models for estimating cost performances, save those for the costs of utilities and consumables, and by-products disposition, are not a function of the individual part processing times. Rather cost performance estimates are calculated using yearly costs and yearly production volumes, and not in an activity based fashion. The 3.7% error in the different cost performance estimates may be attributed solely to the change in quantities of environmental burdens stemming from the use of the different processing times. The overwhelming majority of the manufacturing financial costs are ‘traditional’ machine costs of tooling, consumables, and acquisition, in addition to direct labor. The relative contribution of the financial costs of environmental burdens to the total manufacturing financial cost is quite small and thus little penalty is paid in terms of cost performance accuracy if their inclusion is either omitted or imprecisely conducted.

6.1.4 Findings and Discussion

For this hypothetical example, it is found that though not often included in CAPP systems for process generation, the contribution of auxiliary machinery to overall cost and environmental performances can be quite significant. In Table 16 the percentage contributions to the performance estimates are given by machine type, based on mean results. The contributions to manufacturing performance estimates are important and thus predictive estimates should not neglect the role of auxiliary machinery in proposed processes.

Table 16 Contributions to Part A Performance Estimates by Machine Type

		Primary	Auxiliary
Main	Environmental SPS	61.3%	38.7%
	Financial Cost	69.1%	30.9%
Inventory	Water Use	15.2%	84.8%
	Landfill Waste	23.7%	76.3%
	Recyclable Material	100.0%	0.0%
	Special Waste	22.1%	77.9%
	Energy	61.7%	38.3%
	CO2	61.7%	38.3%

Of particular interest in Table 16 are the significant contributions by the auxiliary machinery in terms of water use and landfill and special wastes generated. Water use and some wastes generated in the manufacturing process may be attributed to the coolant system because it circulates cutting fluid to primary machines, collects spent fluid, and filters wastes from the fluid from reuse. Also, the dust and mist collector specifically collect by-products from the manufacturing process. Given the roles of auxiliary machinery in high volume manufacturing processes, these significant contributions are not altogether surprising, but should certainly be included. It is possible, though not completely correct to model and attribute water use and by-products generation to primary machinery, when in reality they are captured by the auxiliary machinery.

In the face of uncertainty of inputs to the method, sensitivity analyses such as those shown in Table 12, could be particularly helpful in guiding efforts to do more work where it is most impactful. Specifically, findings from sensitivity analyses should be used to highlight (1) 'big hitter' inputs where improvements would have greatest potential in improving costs and environmental performances in manufacturing; and (2) where greatest value is to be realized in reducing uncertainty. An input that has a large bearing on the model outputs should be known fairly well; information gathering efforts should be focused there.

The inventory, cost, and environmental impact outputs as distributions with descriptive statistics, shown in Table 13, are far more insightful into the uncertainties involved in the analysis than deterministic results. This insight is necessary for better understanding of the uncertainty and risks associated with decision making supported by model results. In Table 17, the deterministic outputs directly from the Excel-based tool for each of the manufacturing performance estimates are compared to the probabilistic performance estimates resulting from Monte Carlo simulation. The mean of the probabilistic estimates and the deterministic estimates differ by very little if any amount; the deterministic estimates however lack any insight into the spread, and the uncertainty about that estimate however.

Table 17 Summary Table with Deterministic and Probabilistic Part A Performance Estimates

			MC Output		
		Tool Output	**μ**	**σ**	**units**
Main	Environmental SPS	475	479	48.3	mpt / part
	Financial Cost	5.15	5.41	1.027	$ / part
Inventory	Water Use	0.3	0.3	0.06	gal / part
	Landfill Waste	0.35	0.35	0.075	lb / part
	Recyclable Material	0.16	0.16	0.017	lb / part
	Special Waste	0.35	0.36	0.051	lb / part
	Energy	15.1	15.2	1.53	kWh / part
	CO2	20.20	20.37	2.042	lb / part

Manufacturing performance estimates as distributions with descriptive statistics are far more insightful into the uncertainties involved in the analysis than treating the analysis in a deterministic fashion. Instead of single point, deterministic results, results may be spoken of in terms of probabilities and measures of confidence, such as Type I error α risk, which is far more representative of reality. This is especially useful when results place a designer on the boundary or 'the fence' when it comes to making decisions. Knowledge of the imprecision and uncertainty in the performance estimates can allow decision makers to more fully understand the risk involved in their decisions. For example, say a company wishes to reduce their energy use in manufacturing; they set a design goal (or constraint) for their new part to require no more than 0.75 kWh per piece in manufacturing energy. For the example above, the expected energy use per unit of production is approximately 0.6 kWh, with a standard deviation of approximately 0.10 kWh. With this knowledge, the company is able to determine the confidence level at which they know that they are meeting their energy use goal. A 95% 2-sided confidence interval may be constructed with the known number of iterations, the mean and standard deviation of the energy estimate per part, and the formula for (1-a)100% confidence interval given in Equation 50.

$$x \in \hat{\mu} \pm \varsigma_{\frac{\alpha}{2}} \sqrt{\frac{\hat{\sigma}^2}{n}} \tag{50}$$

For the energy example, the estimate of the mean is 0.6 kWh, the estimate for standard deviation is 0.10 kWh, n is 1200, and for $\alpha = 0.05$, $\zeta_{\alpha/2} = 1.96$. Thus the 95% confidence interval for the energy use per part may be shown to be:

$$\text{Energy} \in \left(\left(0.6 - 1.96 \times \sqrt{\frac{0.10^2}{1200}} \right), \left(0.6 + 1.96 \times \sqrt{\frac{0.10^2}{1200}} \right) \right) = (0.59, 0.61)$$

Which is a fairly tight distribution; it is safe to say that the company's energy goal of using less than 0.75 kWh per unit of production has been met for this part.

Another example would be the comparison of alternative product designs with the intention of selecting the one that is best in terms of cost and environmental performances. The determination of how much better the best design is, or the actual differences between design performances may be ascribed confidence levels. The amount of confidence required to accept a proposed design is left to the discretion of individual decision makers and is not prescribed here. The incorporation of uncertainty yields significantly better understanding of the risks involved and the impacts on decision making, versus blindly following a deterministic result.

Upon the completion of this example for a simple part and manufacturing process, a more complex part and manufacturing processes will be considered in the next example.

6.2 A More Complex Part and Process

A high volume application requires the simple part shown in Figure 71 as a key component; its material is generic steel and the nominal yearly production volume is the same as that of part A: 200,000 per year. The added complexity of this part B, versus part A, is the addition of similar design features with wholly different designs. In addition to precisely meeting the design dimensions, the part must be clean to be successfully integrated into the next level assembly; the cleanliness requirement is met by adding a final washing step to the production process.

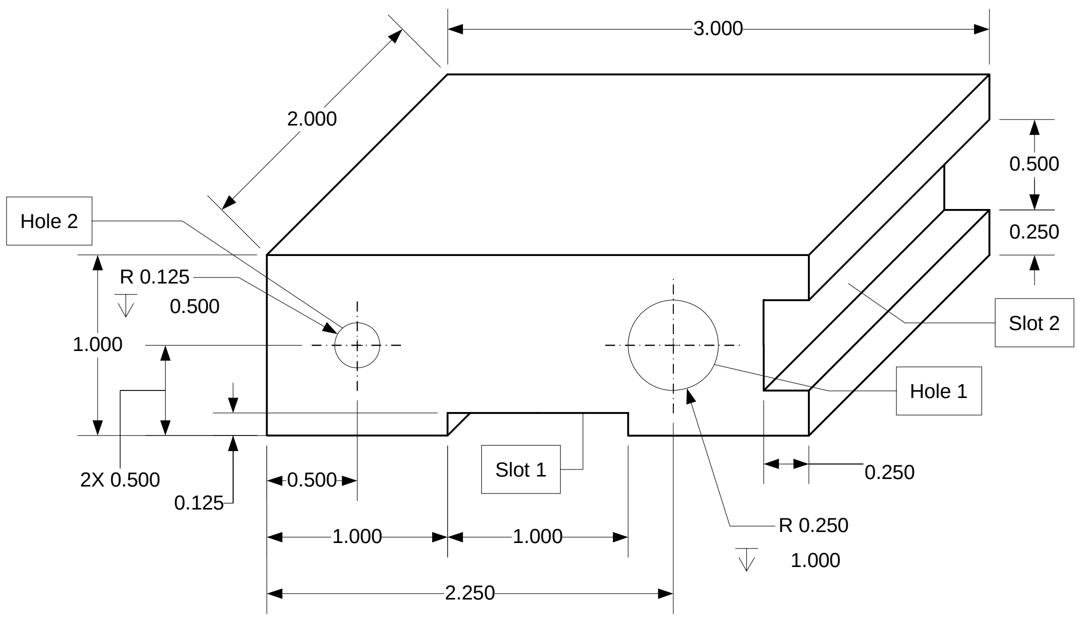


Figure 71 Part B Dimensioned Drawing

The part feature designs in Figure 71 are inputted to the front end of the tool / method, on the left hand side of Figure 12 back in Chapter 3. The specific part features of part B are a hole, with a depth and a diameter, and a slot, with a width and a depth. The feature designs with their dimensions and dimensional tolerances are given in Table 18; these items will be used in the filtering of the available primary machinery in the process generation step. It is assumed that the tolerance level on the feature dimensions is not known, but is greater than 0.001in.

Table 18 Part B Feature Designs

Feature	Dimension (in.)	Tolerance (in.)
Hole 1 Diameter	0.500	>0.001
Hole 1 Depth	1.000	>0.001
Hole 2 Diameter	0.250	>0.001
Hole 2 Depth	0.500	>0.001
Slot 1 Width	1.000	>0.001
Slot 1 Depth	0.125	>0.001
Slot 2 Width	0.500	>0.001
Slot 2 Depth	0.250	>0.001

6.2.1. Process Planning for Part B

For the front end process generation step of Figure 12, a general process is manually selected from all possible means of creating the desired features, and is identical to the process to produce part A, shown in Figure 58 above. The specific configuration of the process may be different however; this situation is addressed in Scenarios 1 and 2 of this section. The process is proposed for manufacturing this part from machined blocks of steel supplied by a vendor. The major dimensions of the blocks are to be held within the allowed tolerances of ±0.005in. by the supplier, and they do so with a very high rate of success. The major processing steps required are milling the slots, drilling the holes, and washing the finished parts; the actual processing order is unknown and it is entirely possible that the holes be drilled before the slots milled. To support this automated high-volume process, coolant systems and mist collectors are required on the milling machines and the drill presses as auxiliary machines.

Though the general processing method for producing part B has been manually selected, the particular machinery to be used must be determined. The same primary and auxiliary production machinery used in part A's process will be used to produce part B, and the Filtering operation of the developed tool will be employed to help guide machine selection. With the addition of additional features of the same type the Filtering operation becomes somewhat more difficult due to the limitations of the developed Excel-based tool. With the current coding, the tool may only consider one of a feature type at a time when filtering the available primary machines in the database. The procedure to determine passing (i.e., capable) primary production machinery is to evaluate the primary machines in the primary database based on part features types which are inputted one at a time. Passing machines are recorded for each round of filtering, and from the passing machines to create each feature the desired primary machinery is selected. An important consideration in the process planning, though not addressed here, is the decision to use individual primary machines to create each feature of the part, or to use more flexible primary machines which are capable of creating multiple features in a single operating step. This difference will be examined somewhat in Scenarios 1 and 2 of this section.

The effects of varying the tolerance levels on the multiple feature designs on the selection of primary production machinery are given in Figures 72 and 73. In Figure 72, the tolerances on the features Hole 1 and Slot 1 are varied and passing machines listed, while in Figure 73 the tolerances on Hole 2 and Slot 2 are varied and passing machines listed. From these lists of passing primary machinery for given tolerance levels on the feature designs, the desired machines must be manually selected.

Tolerance (in.)	>0.01	0.009 - 0.005	0.004 - 0.001
Passing Machines:	Drill Press A	Drill Press A	Drill Press A
	Drill Press B	Drill Press B	Drill Press F
Part features:	Drill Press E	Drill Press F	Milling Machine A
Hole 1	Drill Press F	Milling Machine A	
Slot 1	Milling Machine A	Milling Machine B	
	Milling Machine B	Milling Machine E	
	Milling Machine D	Milling Machine H	
	Milling Machine E		
	Milling Machine H		

Figure 72 Passing Primary Machinery for Tolerance Ranges on 1st Hole and Slot Features of Part B

Tolerance (in.)	>0.01	0.009 - 0.005	0.004 - 0.001
Passing Machines:	Drill Press A	Drill Press A	Drill Press A
	Drill Press B	Drill Press B	Drill Press F
Part features:	Drill Press F	Drill Press F	Milling Machine A
Hole 2	Milling Machine A	Milling Machine A	
Slot 2	Milling Machine B	Milling Machine B	
	Milling Machine D	Milling Machine E	
	Milling Machine E	Milling Machine H	
	Milling Machine H		

Figure 73 Passing Primary Machinery for Tolerance Ranges on 2nd Hole and Slot Features of Part B

For both groupings of part features, the passing machines are nearly identical for each tolerance range; the only difference the passing of Drill Press E for Hole 1, at a tolerance level greater than 0.01in. This fact is due to the feature dimensions all generally falling within the dimensional capability ranges of these primary machines.

The primary machines which do not directly create or affect the part feature designs, but play an important role in the production process, the part washers, must be added to the primary production process. The simplified selection criterion for choosing a washer the ability to meet the required production rates for the part of interest. Given the required hourly production rate of part B is known to be 104, the available part washers in the primary database are manually filtered and the passing machines given in Figure 74.

Passing Washers
A
D
E

Figure 74 Passing Washers for Part B Process

The same auxiliary machinery requirements per primary machine for producing part A are also present here. Given the passing primary machinery to create the features of part B, and the known required auxiliary machinery for those primary machines, the machines chosen for the manufacturing process of part B are given in Figure 75. The machines listed in Figure 75 are the same as those used in the production of part A, but their configuration is potentially variable. The alternative configurations examined in the scenarios are the use of multiple primary machines to create multiple features types, and the sharing of auxiliary equipment between the production lines to produce both parts A and B.

Primary Machines	Auxiliary Machines
Drill Press A	Coolant System A
Milling Machine A	Material Handling A
Washer A	Mist Collector A

Figure 75 Selected Machines to Produce Part B

6.2.2 Scenario 1

In this Scenario the production of part B occurs in isolation and there is no sharing of any production machinery with other production lines. Also, multiple primary machines are employed to create the multiple feature types; that is, there are two milling machines in the process to create each of the two slot features, and two drill presses to create each of the hole features. A mist collector and coolant system each support the multiple primary machines. The process for producing part B under this scenario is given in Figure 76.

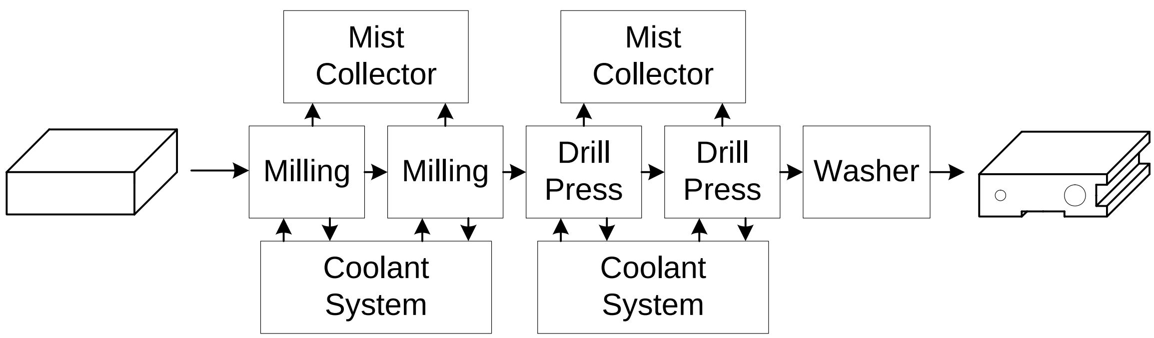


Figure 76 Scenario 1 for Producing Part B

Since the production line for part B essentially exists in isolation and production machinery is not shared between other production lines in this scenario, determining the number of production machines, and the auxiliary hourly production rates is a simple exercise. The number of machines may be determined simply by looking at Figure 76, and the hourly production rates of auxiliary machines by determining the hourly production rates of the primary machines supported by each machine. The number of machines in the process to produce part B, and the hourly production rates of the process are given in Tables 19 and 20, respectively.

Table 19 Scenario 1 Machines in Process to Produce Part B

	Numbers of Machines	
Primary	Milling Machine	2
	Drill Press	2
	Washer	1
Aux	Mist Collector	2
	Coolant System	2
	Material Handling	6

Table 20 Scenario 1 Hourly Production Rates

Hourly Production Rates	
Mist Collector	208
Coolant System	208
Material Handling	104
Production Line	104

Using the generated process shown above, the same machine database inputs as for part A, the numbers of machines, and the auxiliary production rates, all under the same stated assumptions as for part A, manufacturing performance estimates are generated using the Excel tool and by Monte Carlo simulation. The manufacturing performance estimates for producing part B with the production process given above for Scenario 1, are presented in Table 21.

Table 21 Scenario 1 Part B Manufacturing Performance Estimates

			MC Output		
		Tool Output	**μ**	**σ**	**units**
Main	Environmental SPS	511	514	56.1	mpt / part
	Financial Cost	5.68	5.95	1.069	$ / part
Inventory	Water Use	0.2	0.2	0.03	gal / part
	Landfill Waste	0.29	0.29	0.047	lb / part
	Recyclable Material	0.31	0.31	0.034	lb / part
	Special Waste	0.31	0.31	0.040	lb / part
	Energy	16.4	16.5	1.78	kWh / part
	CO2	21.88	22.02	2.382	lb / part

Again it is seen that the deterministic Excel tool estimates are nearly identical to the mean of the Monte Carlo estimates, but they lack any insight into the spread and uncertainty of the performance estimates. It will be interesting to compare the performance estimates of parts A and B, but this will be done after examining another potential configuration of their production processes in Scenario 2.

6.2.3 Scenario 2

In this Scenario the production of part B does not occur in isolation and there is sharing of the auxiliary production machinery with the production line of part A. The production line for part A remains unchanged from the previous example, but the production line for part B has been altered. Only one of each type of primary machine is employed to create the multiple feature types; that is, there is one milling machine in the process to create each of the two slot features, and one drill press to create each of the hole features. Without knowing the inner workings of these primary machines, and making the assumption that they have the flexibility and capability of creating multiple features in a single, automated operation, their typical processing time has been multiplied by two to consider the additional feature creation. The actual processing time for creating multiple features in a single operation step is necessary to more accurately predict the machine's performance. A mist collector and coolant system each support the primary machines from both production lines. The combined process for producing parts A and B under this scenario is given in Figure 77.

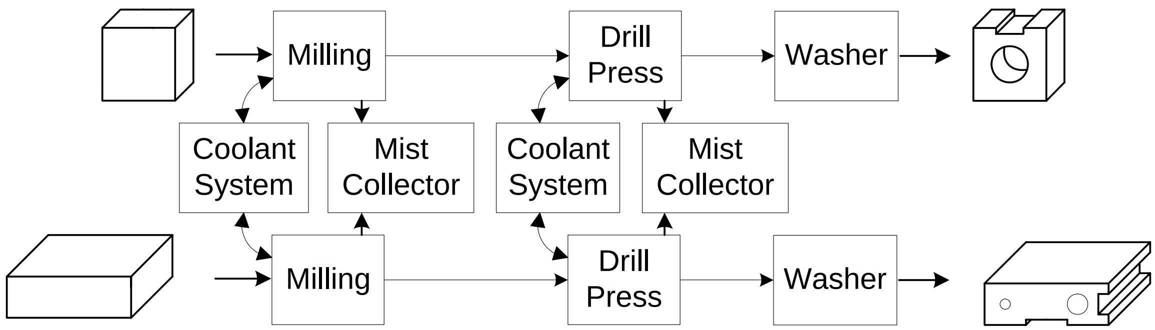


Figure 77 Scenario 2

Since the production line for part B does not exist in isolation and production machinery is shared between the production line for part A in this scenario, determining the number of production machines, and the auxiliary hourly production rates is a bit harder than the previous examples. Due to the equivalent production rates however, the assumption may be made the sharing of the auxiliary equipment is equivalent, which simplifies the calculation of machine fractions considerably. The number of machines may be determined easily enough by looking at Figure 77, but machine fractions for the shared auxiliary machinery must be calculated to properly attribute machine performance to the production lines of interest. The number of machines in the processes to produce parts A and B are given in Table 22, and the calculation of the machine fractions for the shared mist collectors and coolant systems follow the table.

Table 22 Scenario 2, Machines for Processes to Produce Parts A & B

		Part A	Part B
Primary	Milling Machine	1	1
	Drill Press	1	1
	Washer	1	1
Aux	Mist Collector	2	
	Coolant System	2	
	Material Handling	4	4

Machine fractions for shared auxiliary machinery, under the assumption of equal support of primary machinery, may be calculated using Equation 14 from Chapter 3. For both parts A and B, the machine fractions for the mist collectors and the coolant systems are equivalent and equal to 1, by:

$$f_A = f_B = 2 * (2 / 4) = 1$$

Though the mist collectors and coolant systems are shared by the two production lines, and used to support different primary production processes, essentially these machine fractions may be interpreted to mean that one mist collector and one coolant system is used to support the primary processes on each production line. A quick double check, summing the machine fractions should equal the total number of each auxiliary machine type; 1 + 1 = 2 and thus the machine fractions for the auxiliary machines are reasonable.

The hourly production rates of auxiliary machines are determined from the hourly production rates of the primary machines supported by each machine. The hourly production rates of the auxiliary machines are given in Table 23; these rates are for each instance of a machine in the processes.

Table 23 Scenario 2, Auxiliary Hourly Production Rates for Parts A & B

	Part A	Part B
Mist Collector	208	
Coolant System	208	
Material Handling	104	104
Production Line	104	104

Using the generated process shown above, the same machine database inputs as for part A, the numbers of machines, machine fractions and the auxiliary production rates, all under the same stated assumptions as for part A, manufacturing performance estimates are generated using the Excel tool and by Monte Carlo simulation. The manufacturing performance estimates for producing part A and part B, with the production process given above for Scenario 2, are presented below in Table 24 and 25, respectively.

Table 24 Scenario 2, Part A Manufacturing Performance Estimates

			MC Output		
		Tool Output	μ	σ	units
Main	Environmental SPS	382	384	37.3	mpt / part
	Financial Cost	4.23	4.41	0.787	$ / part
Inventory	Water Use	0.1	0.1	0.01	gal / part
	Landfill Waste	0.17	0.17	0.022	lb / part
	Recyclable Material	0.16	0.16	0.017	lb / part
	Special Waste	0.16	0.16	0.018	lb / part
	Energy	12.2	12.3	1.18	kWh / part
	CO2	16.31	16.37	1.583	lb / part

Table 25 Scenario 2, Part B Manufacturing Performance Estimates

			MC Output		
		Tool Output	μ	σ	units
Main	Environmental SPS	450	451	43.8	mpt / part
	Financial Cost	4.42	4.61	0.818	$ / part
Inventory	Water Use	0.1	0.1	0.02	gal / part
	Landfill Waste	0.22	0.22	0.028	lb / part
	Recyclable Material	0.31	0.31	0.034	lb / part
	Special Waste	0.23	0.23	0.027	lb / part
	Energy	14.5	14.5	1.40	kWh / part
	CO2	19.31	19.37	1.864	lb / part

Again it is seen that the deterministic Excel tool estimates are nearly identical to the mean of the Monte Carlo estimates, but they lack any insight into the spread and uncertainty of the performance estimates. This more complex product and process example could perhaps be made more interesting by adding sharing of the final washers for the two parts, and by varying the production rates such that the production volumes for the two parts are not equivalent to yield non-integer machine fractions. Also, the use of one coolant system and one mist collector for all primary processing machines may be added. In the next section, the estimates generated for each part and the different scenarios will be compared and discussed.

6.2.4 Comparison of Scenarios and Discussion

In this section comparisons will be made using deterministic tool outputs for manufacturing performance estimates. The differences in performance for both of the production lines when operated, (1) independently of each other, and (2) while sharing auxiliary machinery, will be presented. Also, the differences in performance between the two parts when produced while sharing auxiliary equipment will be discussed. The comparisons of Part A and Part B in the different production scenarios are given in Tables 26 and 27, respectively.

Table 26 Part A Manufacturing Performance Comparison

		1st Example	2nd Example Scenario 2	units	% Reduction
Main	Environmental SPS	475	382	mpt / part	19.5%
	Financial Cost	5.15	4.23	$ / part	17.8%
Inventory	Water Use	0.3	0.1	gal / part	56.7%
	Landfill Waste	0.35	0.17	lb / part	52.0%
	Recyclable Material	0.16	0.16	lb / part	0.0%
	Special Waste	0.35	0.16	lb / part	53.2%
	Energy	15.1	12.2	kWh / part	19.3%
	CO2	20.20	16.31	lb / part	19.3%

Table 27 Part B Scenario Manufacturing Performance Comparison

		Scenario 1	Scenario 2	units	% Reduction
Main	Environmental SPS	511	450	mpt / part	11.9%
	Financial Cost	5.68	4.42	$ / part	22.2%
Inventory	Water Use	0.2	0.1	gal / part	35.1%
	Landfill Waste	0.29	0.22	lb / part	24.6%
	Recyclable Material	0.31	0.31	lb / part	0.0%
	Special Waste	0.31	0.23	lb / part	24.3%
	Energy	16.4	14.5	kWh / part	11.7%
	CO2	21.88	19.31	lb / part	11.7%

There are across the board improvements in manufacturing performances when the parts are not produced in isolation; smaller values for each of the indicators are suggestive of improvements in manufacturing performance. Assuming constant work load of machinery (i.e., constant machine operating characteristics), sharing machinery between production lines will always improve per part manufacturing performances.

Essentially, value is increased by increasing the benefit (i.e., produced parts) realized for the same financial and environmental investments. Recyclable material generated is seen to remain constant in both comparisons above as expected given that no part design change has been made, but landfill and special wastes generated incorrectly reduce. The reduction in the generation of these by-products is predicted because of the assumption of constant machine operating characteristic, regardless of work performed. While this assumption may hold true for utilities and resource consumption, which may be thought of as open loop feedback systems (i.e., regardless of operating conditions or work load, the machine will exhibit identical behavior. A clothes washing machine is an excellent example; regardless of the level or presence of clothing, a wash cycle is performed identically every time), this assumption is not valid for by-products generation. If one mist collector is used to support two primary machines on different production lines instead of one, it should be expected that the machine will collect twice the amount of by-products as it did previously. In sharing situations the typical environmental burden rates values for by-products generation of primary and auxiliary machinery should be updated to reflect reality. The reductions in by-products in Tables 24 and 25 should be approximately zero because of the sameness of the product designs and thus material removed in manufacture.

The direct comparison of Parts A and B in Scenario 2 of the 2nd example is given in Table 28.

Table 28 Scenario 2 Parts A & B Manufacturing Performance Comparison

		Part A	Part B	units	% Increase
Main	Environmental SPS	382	450	mpt / part	17.7%
	Financial Cost	4.23	4.42	$ / part	4.5%
Inventory	Water Use	0.1	0.1	gal / part	0.0%
	Landfill Waste	0.17	0.22	lb / part	32.6%
	Recyclable Material	0.16	0.31	lb / part	98.2%
	Special Waste	0.16	0.23	lb / part	40.6%
	Energy	12.2	14.5	kWh / part	18.4%
	CO2	16.31	19.31	lb / part	18.4%

Across the board there is a worsening of manufacturing performance for Part B over Part A; larger values for each of the indicators are suggestive of decline in manufacturing performance. Looking at Figure 77 above, the production processes for parts A and B are identical in number and the auxiliary machinery are shared equally. The differences then are attributable solely to the increase in processing times required to create the additional part features of part B. Adding features to part designs increases the complexity in not only the part, but also its production process, and degrades both the part's cost and environmental performance in manufacturing. The same caveat regarding by-products generation needs mentioning however; though the designs of the two parts are different, the material removed from each, and the resulting amounts of by-products generated should be checked, as it is not simply a function of processing time. Rather it is a function of the completion of a machining process.

6.3 Thesis Roadmap

In this chapter two illustrative examples were presented to exercise the method proposed in this thesis, and the developed Excel-based tool, in a predictive fashion. The cost and environmental performances of the manufacture of two simple part designs was estimated using the method. By exercising the different aspects of the method with these hypothetical examples, Empirical Performance Validity has been partially established, though the inability to verify or validate the numerical manufacturing performance estimates degrades this somewhat. In the following chapter, a study of automotive transmission pinion gear design and manufacture, with real manufacturing machinery data and information, is conducted as a further attempt to demonstrate and establish the Empirical Performance Validity of the proposed method.

CHAPTER 7

A STUDY OF AUTOMOTIVE TRANSMISSION GEAR DESIGN AND MANUFACTURE

In this chapter the design and ensuing manufacturing performances (cost and environmental) of automotive transmission pinion gears are discussed and the tool developed in this thesis applied. The developed Excel-based tool is used to 1) assess the manufacturing performances of two implemented pinion gear production processes, and 2) predict the manufacturing performances of pinion gear designs at an early stage of product design when process plans are not well defined. Before jumping into the analysis of the manufacture of pinion gears the motivation for doing so is established by discussing the effects of design of automobiles and their components on the environment. Also, gear tolerances and design, and their implications on noise, vibration, and harshness (NVH), a key automobile performance characteristic, as well as an overview of gear manufacturing methods are given.

Two common methods for producing transmission gearing with differing tolerance design specifications are each analyzed using the developed tool. Green finishing, a preferred method of gear manufacture, produces gears with greater variation in gear geometry features, while hard finishing is able to achieve more accurate gear geometries by 'finishing' the gears post-heat treatment hardening, which introduces distortion. Actual gearing production data and information provide the basis of these assessments and comparisons. The chapter wraps up with an example of an early design phase analysis when very little process plan information is known.

7.1. Effects of the Design of Automobiles and Components on the Environment

With growing human populations and increasing standards of living, the number of automobiles is expected to grow exponentially in the coming years. Automobiles are one of the most important innovations ever to be introduced to human society. Their impacts can not be easily understated; daily human existence and life has been forever altered by changing the ways people travel, work, do business, and leisure. Since these automobiles tax our limited environment and resources to such a large degree, efforts must be undertaken to make these vehicles more environmentally-friendly in all aspects of their life cycle, from materials production through vehicle assembly to vehicle use and at end-of-life. Additionally, as carmakers face increasing competition in all markets, from those of developing parts of the globe to those in the more mature markets of North America and Europe, they seek to optimize costs in all life cycle phases of their products in order to achieve sustainable competitive advantage.

The use phase of the automobile has the greatest impact, in the form of emissions, on the environment of the automobile's life cycle phases (Sullivan, et al. 1998), and thus new, cleaner technologies and energy sources are sought to reduce vehicle emissions. However, impacts of other life cycle phases of the automobile, its component systems, and its larger auxiliary systems and infrastructure (e.g., manufacturing, sales distribution, service and repairs, road systems, fueling, etc.) are not insignificant or problematic. The environmental performance of component manufacture not been studied to the same degree that other life cycle phases of the automobile system currently have been; besides the aforementioned use phase, the end of life phase has received considerable attention (re / de manufacturing, recycling, materials recovery and reuse, etc.) as a promising area in which to improve vehicle environmental performances. Also, the use of recycled materials, or novel, more sustainable bio-materials has been studied and implemented in industry. Though perhaps not so much of a 'big hitter' as other environmental performance improvement initiatives in other life cycle phases, automotive component manufacture is not without negative impacts on the environment, and requires attention as well. Additionally, the cost of manufacturing is a significant contributor to the total cost of the realization of an actual vehicle. Improvements in cost and environmental performances of a gear in manufacturing are likely to be enhanced through the design of the gear itself. To accomplish this feat, designers need capabilities to predict the costs and environmental impacts of their designs in order to make more informed decisions with respect to these goals.

The automatic transmission is a key and very complex component of a modern vehicle's powertrain system; itself made up of many components. The definition of a powertrain is the system of components and subsystems which transmit a vehicle engine's output power to its wheels, and for vehicles includes the engine, transmission, clutch, drive and axle shafts, differential, universal joints, and differential gear (2003). The transmission plays a very important role in the overall performance of a vehicle; fuel efficiency, acceleration, power, smoothness of ride, and noise, vibration, and harshness (NVH) are all strongly affected by the design of the transmission. Cutaway views of modern automatic transmissions are given in Figure 78 (Hulsey visited June 8, 2006), and Figure 79 (courtesy of Ford Motor Company), below.

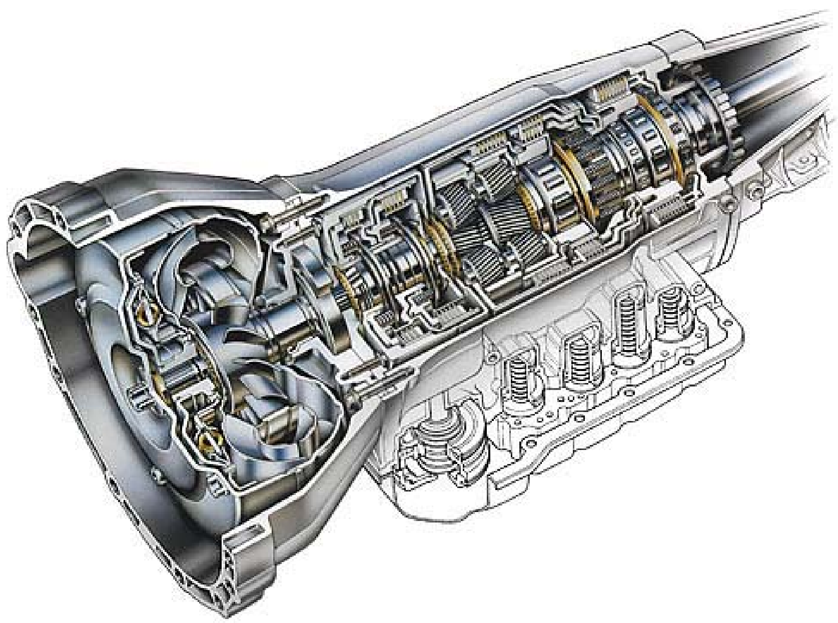


Figure 78 Cutaway View of an Automatic Transmission

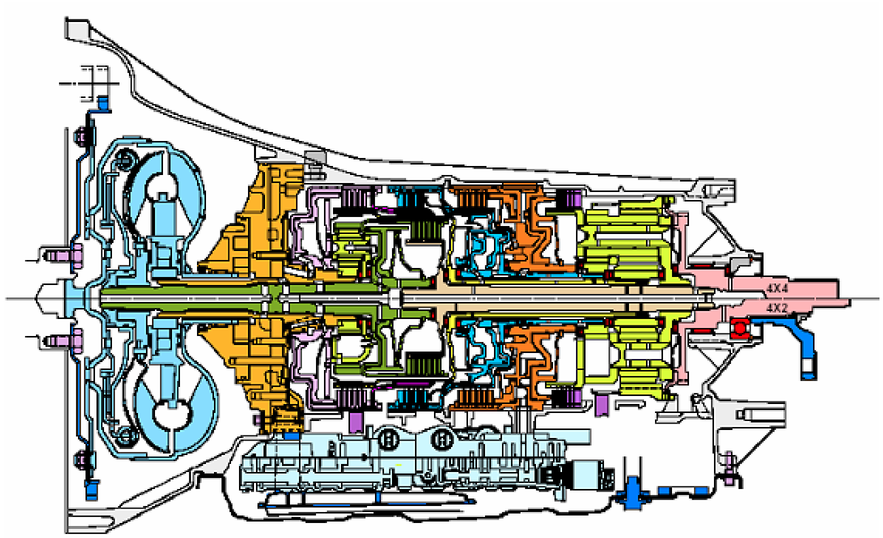


Figure 79 Another Cutaway View of an Automatic Transmission

The main component systems of an automatic transmission are the gearing (typically in a simple, planetary configuration), torque converter, case, shafts and bearings, and a hydraulic system which includes pumps, fluid, and a valve body which acts to control fluid flows to the clutches and brake which control the power flow through the transmission. The valve body in modern vehicles is most often controlled by an electronic transmission controller. The many component systems of the transmission work to achieve its main function of automatically changing the gear ratios for varying powertrain output torques to the wheels of the vehicle, allowing the engine to work most efficiently for different driving speeds. While each of the many components of an automatic transmission pose their own unique and difficult design challenges, and the design and manufacturing cost and environmental performances of each could be discussed at length, the design and manufacture of the transmission gearing will be examined here. Specifically, of the gearing present in automatic transmissions and transaxles (ring gears, sun gears, planetary (pinion) gears, and final drive gears), the pinion gears are of the focus of this case study.

To place the design and manufacture of transmission gearing in the context of the rest of the automotive system, a 'Vee' diagram (Aughenbaugh, et al. 2004) is given in Figure 80. It may be seen that the requirements specified for gear design are a results of a 'flowdown' of requirements from a vehicle level, to the powertrain level, to the transmission level and then finally down to the component level of the gearing. This traverse down the left hand side of the Vee is called decomposition, and steps down levels of abstraction of the automotive system. The right half of the Vee in Figure 80 is the integration of the various components into higher level assemblies and systems, and ultimately into the vehicle that is delivered to the marketplace. The lighter arrows and boxes indicate other decomposition and integration paths that exist and must be addressed, but are not addressed here. Similarly, for the components of the transmission system other than the gearing, there exist the necessary process planning (the link between design and manufacturing) and manufacturing operations, from which the components join in the integration up the right hand side of the Vee. At each level of decomposition, there may exist concurrent design efforts similar to the map present in Figure 1, in Chapter 1.

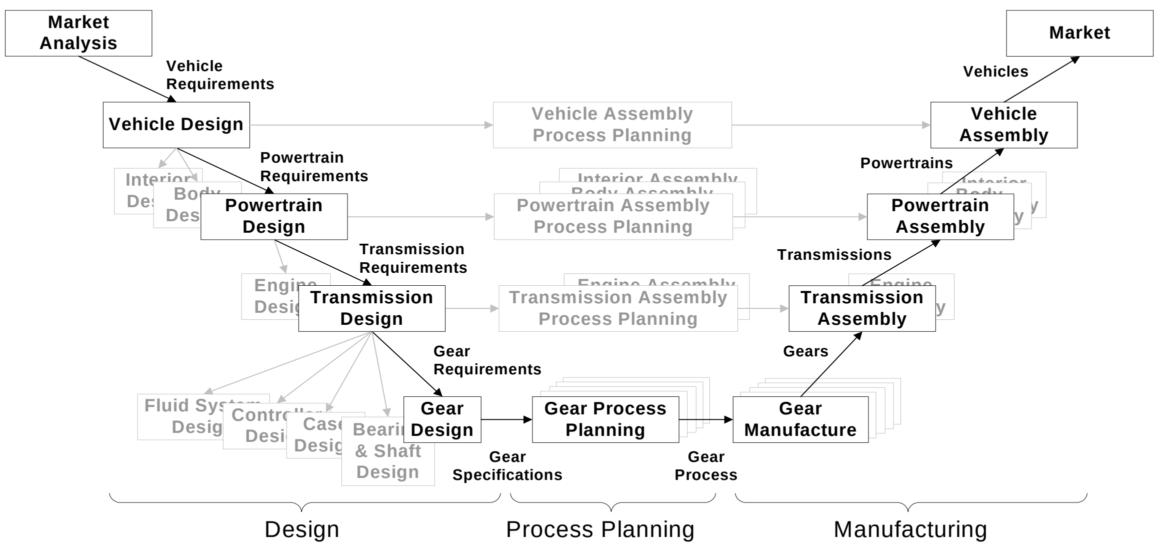


Figure 80 Systems Vee Diagram for Automotive Components Design

Decisions made at higher levels on the left hand side of the Vee in Figure 80 can have significant effects on lower level designs; not only should a predictive method for estimating manufacturing performances be utilized at the component design level, but should also be used to push feedback information up the chain to connect systems level design decision making to performances in the manufacturing phases of a product system's life cycle. Higher level decision making has the greatest leverage for improving lower levels performances. Of course tradeoffs between other design objectives and requirements while remaining within constraints is also necessary.

7.2 Gear Noise, Tolerances, and Design

NVH (noise, vibration, and harshness) is a key performance characteristic of automobiles that is directly tied to customer satisfaction and thus the financial performance of the car maker. Due to the very complex and somewhat subjective nature of NVH, as well as the great length of design and manufacturing planning cycles of automakers, components that affect NVH such as transmission gearing are possibly over-designed by specifying ultra-smooth surface finishes and tight tolerances, in hopes of avoiding last minute costly, reactive, and corrective measures. In the pursuit of superior NVH levels, high precision gears are specified for use in transmissions; the manufacturing costs and environmental impacts of the precise machining operations, namely grinding and honing of teeth profiles after heat treatment hardening, required to produce these gears are considerable.

Additional costs are clearly incurred with the introduction of these machining process steps and environmental impacts result from the waste products and additional resources consumption of these operations. While the financial costs of additional machining process steps are typically considered, the environmental effects are commonly neglected. This neglect leads to situations where design decisions are made without the knowledge of environmental costs associated with a product or process, an undesirable situation given the increasing importance and awareness of the cause of environmental sustainability. Before performing the analysis of the cost and environmental performances of transmission gear manufacture, gear noise and how it relates to the design and specification of tolerances of gears warrants discussion.

7.2.1. Gear Noise

Gear noise is a common item of concern in almost any application involving gearing. The differentiation between sound and noise can be defined simply: sound is a variation in pressure; noise is undesired sound. Noise may be defined simply as any unwanted or undesired sound (AGMA 2004); thus gear noise may be defined as the unwanted sound caused by the interaction of gears. In industrial applications, noise from gear boxes must be below certain noise levels, measured in decibels (dB), to protect the safety of workers' hearing. In other applications, gear noise is simply unwanted by the user or customer, for reasons ranging from stealth to luxury and comfort demands. Additionally, gear noise is often an indicator, either real or perceived, of wear, and potential failure / break down of the gearing system. In the case of automobiles, customers want quiet and smooth rides in their vehicles; failure to achieve this builds a perception of 'cheapness', lack of quality, and undesirability which will hurt sales, and thus the financial performance of a car maker. Because of these facts, car makers attempt to reduce NVH levels in many areas of vehicle design, by addressing factors in each of the system levels shown in Figure 80. A car exists in an inherently noisy environment (e.g., wind noise, other traffic) and creates its own noise via its engine and transmission systems; thus addressing the design challenges of providing customers and their passengers with a quiet and comfortable internal vehicle environment are substantial. One of the many approaches taken is reducing gear noise within the automatic transmission.

7.2.1.1. Sources of Gear Noise

According to the American Gear Manufacturers Association (AGMA), gear noise is most often generated by the mesh action of the gear teeth (AGMA 2004). Irregularities in tooth profile or spacing will cause noise to be generated at the frequency of those irregularities. Completely accurate (theoretical) tooth profiles still generate gear noise due to the dynamics of gear meshing; the noises generated often occur at the frequency of meshing, harmonics of that frequency, or at sideband frequencies (AGMA 2004).

Transmission error (TE), defined as the difference between the actual position of the output gear and the position it would occupy if the gears were perfectly conjugate, is the single most important factor in the generation of gear noise (Houser 1992). Manufactured transmission error (MTE) is affected most by profile inaccuracies, spacing errors, and gear tooth runout (Houser 1992), a measure of a gears accuracy and precision. The dimensional variations which result primarily from manufacturing, but also from deflections in operation (AGMA 1993) are the primary culprit for noise generation. Other sources of gear noise include changes in mesh stiffness, impacts of gear teeth at the initiation of tooth contact, dynamic mesh forces, frictional force effects, pocketing of air, lubricant entrainment (Houser 1992), and increases in speeds and loads (AGMA 2004).

It becomes apparent that noise generation in gearing is primarily related to the precision of gearing and the operation of that gearing. Thus, for 'quiet' gearing, precise gears with tight tolerances on design features are desired. However, looking beyond the noise implications of gear meshing effects, gear noise is also a system level issue. Gearing never exists in a vacuum; it is always integrated into some system of power transmission. In fact, according AGMA, identical gear units will most likely generate completely different noise levels when installed in different systems (AGMA 2004).

An automobile's automatic transmission is a perfect example. The following is adapted from AGMA's explanation of the integration of a gear unit into a larger system for the gearing in an automatic transmission, placed in a vehicle. When an automobile's transmission is actually assembled to the vehicle's engine and installed in the vehicle, the prediction or estimation of the transmission gearing noise is difficult, since it is now part of a noisy acoustic system which also includes, the engine (the prime mover), driven equipment (the drive shaft), transmission mounting, and the surrounding acoustic environment (AGMA 2004). Additionally, the placement of 'perfect' transmission gearing into a vehicle will still have noise problems, while less precise transmission gearing, when assembled into another vehicle, will have acceptable noise performance.

The system level of noise and automobile NVH is partly explained by the two methods of sound (and noise) transmission. Structure-borne sound travels at least part of a path by vibrations through a solid structure, while airborne sound travels solely by propagation through air. Structure-borne sounds may excite natural resonances of other structures and equipment in the system, and thus create noise levels greater than the geari noise source of interest. For example, structural resonant frequencies of the transmission casing may be excited by gearing (internally) generated frequencies to produce noise. Designers must attempt to determine natural frequencies of the support structures, such as carrier assemblies, transmission cases, and mounts, to ensure that rotational and other generated frequencies are not synchronized to, or a multiple of, natural frequencies (AGMA 2004).

Common sources of airborne and structure-borne noises generated in gearing systems include: balance, alignment, friction, looseness, distortion, critical speeds, resonances, tooth mesh, tooth contact, bearing instability, system pulses, and windage (AGMA 2004). The sources of airborne and structure-borne noises are very important considerations when design gears and their integrated systems for noise control.

7.2.1.2. Controlling Gear Noise

To address gear noise, approaches to control both airborne and structure-borne noise generation must be taken. According to Houser and Sorianto however, noise minimization of gearing is seldom considered in great detail at the initiation of a design, but is often considered only when noise becomes a problem (Houser, et al. 2002).

To address structure-borne noise issues, the design of housings and cases, other surrounding elements, and the selection of materials based on abilities for insulating, isolating, and / or damping could prove to be beneficial in reducing noise levels. Also, controlling or altering the noise transmission path through the surrounding system (an automobile) can reduce noise levels perceived by vehicle occupants. This may be accomplished by interrupting or changing the direction of the transmission path of noise.

Alternatively, the heart of the issue may be addressed by attempting to control the source of the noise: the gears themselves. Gears of higher quality, which is indicative of tighter tolerances and higher precision, as defined by AGMA and DIN, tend to produce less noise. Reducing noise at the source requires changes in the design of the gearing and / or improvements in manufacturing quality. The method chosen for noise control often depends on the economics involved (AGMA 2004), which are not always clear given the ‘walls’ between different system levels and process planning, but the decision should perhaps also include environmental considerations!

There are a number of design features relevant for considering noise control, according to Hoppe and Pinnekamp (Hoppe, et al. 2004), and AGMA (AGMA 2004):

- Structure-borne considerations: bearings, housing, separation of noise source and dissipating housing areas, and type of gearing, unbalance and alignment, type of bearing support;
- Gear macro geometry: number of teeth, module, helix angle, overlap ratio, transverse contact ratio, design load vs. operation , gear blank design, tooth ratios, pitch line velocity, etc.;
- Gear micro geometry: surface accuracy, lead modification, profile modification, pitch, pressure angle, total gear contact ratio, quality;

7.2.2. Gear Tolerances and Design

Gears are complicated mechanical components with complex geometries that experience dynamic loadings and stresses; designing gears to minimize noise issues as just discussed, along with meeting numerous other design requirements and objectives such as manufacturability, reliability, cost minimization, and not to mention performing well in service, is not an easy task. The difficulties in adding an additional consideration of the environment to gear design are perhaps therefore somewhat understandable. Designing gearing for automotive transmission is certainly no exception; an added challenge in designing gearing for vehicle use is that the loadings are not constant but highly variable (AGMA 1993, Dudley 1994).

AGMA says that the range of gears typically used in vehicle applications are between AGMA Quality numbers 7 and 12 (AGMA 1993), while other authors say that range is narrower, between 10 and 11 (Smith 1992, Ewert 1997). AGMA, and DIN, have published standards specifying the allowable tolerances for unassembled gears; excerpts from these standards, for helical gears of similar size ranges to the pinion gears of this case study, are presented along with the definitions of many gear feature tolerances, in Appendix B. AGMA and DIN assign quality numbers to classify gears which have certain requirements on key items such as runout, pitch, profile, and lead. As AGMA quality numbers increase, tolerances on gear features tighten; the DIN classifying scheme works inversely, as quality numbers increase, tolerances on gear features become more loose. It is recognized in gear design that tighter tolerances are more expensive to achieve, and thus design rules abound whereby designers are warned not to select higher quality gearing than is actually necessary for the application. Sometimes higher quality gears will be needed however; the tradeoff decision between improved performance and increased cost of the gearing should have rigorous justification to prevent an over-design situation.

Many features of a gear require tolerance allocations. The macro-design parameters, such as bore and outer diameters, face width, and surface flatness, among others, which largely influence how well the gear integrates with the next level assemblies (e.g., carrier and transmission), though not unimportant, are not as critical as the micro-design parameters related to the gear teeth when it comes to noise concerns and gear quality. Care must be taken when specifying the tolerances for both levels of a gear's design. AGMA and DIN Quality numbers are set based on the tolerances on micro-design features. The quality of gear teeth can not be completely controlled until appropriate tolerances are specified on the following items (Dudley 1994): tooth spacing, tooth profile, concentricity of teeth with axis, tooth alignment (or lead or helix), tooth thickness (or backlash), and surface finish of flank and fillet. Transmission gear designers typically need to fine-tune their designs to a greater degree than simply setting an AGMA or DIN quality number allows for, and thus on gear print drawings the unique specifications for the critical tolerance items will be given.

References exist to assist gear designers in understanding the accuracy limits for the particular design features in the list above. An example is Dudley's Handbook of Practical Gear Design (Dudley 1994); an excerpt of commonly understood accuracy limits on gear features is given in Appendix B.

7.3. The Pinion Gears of the Case Study

The pinion gears of the case are introduced in this section. There are six unique helical pinion gear designs which will be examined and come from two different automatic transmissions; both transmissions are newer 6-speed models to appear in vehicles in upcoming model years. The key advantage of a 6-speed automatic transmission, over the currently more common 4- or 5-speed, is better fuel economy by allowing the engine to operate most efficiently in a greater range of vehicle speeds. One of the transmissions is for rear wheel drive (RWD) vehicles, with its gearing in the more complex, Ravigneaux configuration. The other is a front wheel drive (FWD) transaxle, whose gearing is in a simple planetary configuration, and also includes the final drive gears located in the rear for RWD vehicles. Essentially, a Ravigneaux configuration connects planetary gear sets with common, longer pinions; in an automatic transmission there are a few planetary assemblies which are used to achieve the desired gear ratios of the transmission, though typically these gear sets are not connected by common pinion gears. Depictions of a Ravigneaux and simple planetary gear set configurations are shown in Figure 81 (Arques visited June 8, 2006, Edwards visited June 8, 2006).

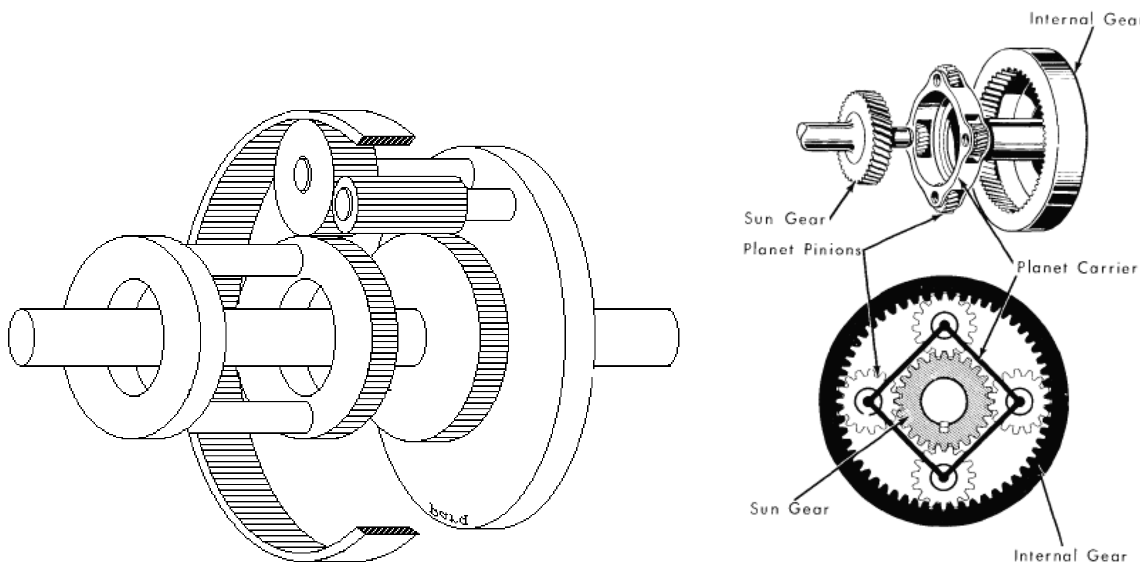


Figure 81 Ravigneaux (left) and Simple Planetary (right) Gear Sets

The pinion gears of the two transmissions share many of the same processing steps in manufacture, but differ substantially in their finishing. Those of the FWD transaxle are ‘green’ finished; that is, their tooth profiles are ‘finished’ while the gears are still green, or soft, prior to heat treatment hardening. Those of the RWD transmission are ‘hard’ finished; their tooth profiles are finished after the gears have been hardened in the heat treatment processing step. The heat treatment step, which is necessary to sufficiently harden the gears for long life, introduces some distortion or warping of gear geometries, specifically tooth profiles. Depending on the tolerance / accuracy requirements of the gear design, the heat treat induced distortion may or may not be within allowable levels. A requirement for more precise gearing will often necessitate the use of a hard finishing process since it affords better control and accuracy of production gears. Some example automotive transmission pinion gears are shown below in Figure 82.

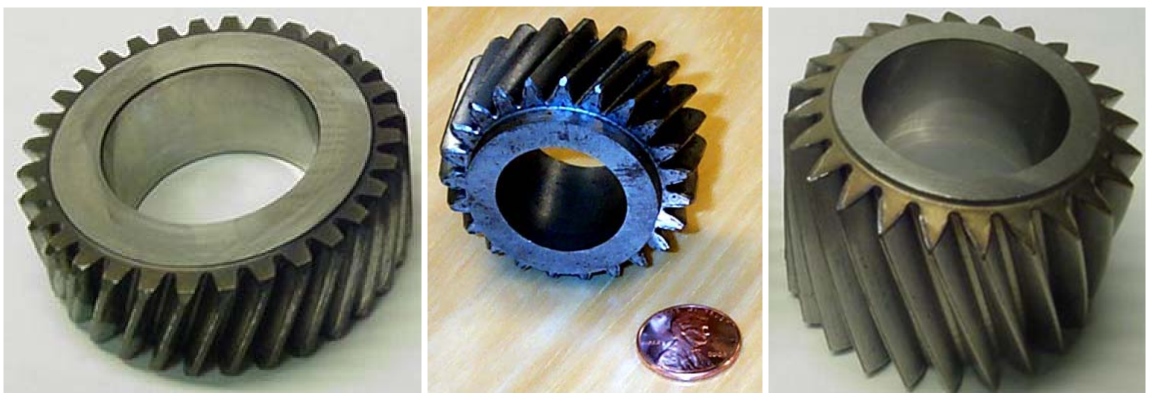


Figure 82 Example Pinion Gears

Macro-design parameters of the six pinion gears of interest in Table 29 below give an idea of the gears' relative sizes. Pitch diameter may be defined as the diameter of the pitch circle of a gear, which is the circular path from a point on one gear tooth to a like point on the next tooth (Dudley 1994); circular pitch is that distance between the two points on that arc. The gear height is simply the height of the gear teeth when the gear is laid on its flat face surface; from gear height, face width is calculated using the angle of the helix, also given in Table 29. The numbers of teeth, which determine the available gear ratios of the automatic transmission, are also given to be used in the calculations of diametral pitch and module, which follow Table 29.

Table 29 Macro Design of Pinions of Interest

<table>
<tr><th></th><th>Gear</th><th>Pitch Diameter (mm)</th><th>Gear Height (mm)</th><th>Helix Angle (deg)</th><th>Face Width (mm)</th><th>No. Teeth</th></tr>
<tr><td rowspan="3">Green</td><td>Reaction Pinion</td><td>57.78</td><td>17.50</td><td>22.50</td><td>18.94</td><td>32</td></tr>
<tr><td>Input Pinion</td><td>32.65</td><td>17.40</td><td>21.00</td><td>18.64</td><td>24</td></tr>
<tr><td>Output Pinion</td><td>35.88</td><td>17.80</td><td>18.00</td><td>18.72</td><td>29</td></tr>
<tr><td rowspan="4">Hard</td><td>Rear Short Pinion</td><td>43.46</td><td>35.05</td><td>20.15</td><td>37.34</td><td>24</td></tr>
<tr><td>Rear Long Pinion 1</td><td>41.65</td><td>20.45</td><td rowspan="2">20.15</td><td rowspan="2">21.78</td><td rowspan="2">23</td></tr>
<tr><td>Rear Long Pinion 2</td><td>41.65</td><td>35.15</td></tr>
<tr><td>Front Short Pinion</td><td>27.03</td><td>22.95</td><td>19.77</td><td>24.39</td><td>16</td></tr>
</table>

Before calculating modules and diametral pitches, it should be noted that the hard finished ‘rear long pinion’ from the RWD transmission with the Ravigneaux gear configuration is a special design whereby there are two sections on the same part with teeth; this unique design is required to connect two adjacent planetary gear sets in the Ravigneaux configuration. The rear long pinion is sketched in Figure 83, with the two tooth regions labeled.

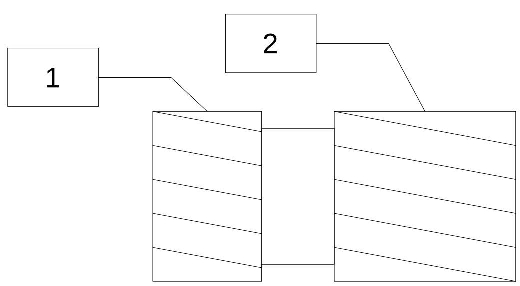


Figure 83 Rear Long Pinion

Normal module and diametral pitch are used by DIN and AGMA as part of their quality classification schemes, respectively. From the number of teeth and pitch diameter, the transverse diametral pitch may be calculated using Equation 51, and the normal diametral pitch using Equation 52.

$$P_d = \frac{N}{d} \tag{51}$$

$$P_{nd} = \frac{P_d}{\cos(\text{helix angle})} \tag{52}$$

In Equation 51, N is the number of teeth, and d is the pitch diameter. Diametral pitch, P_d, is defined as the number of teeth per inch of pitch diameter, and the units for this standard measure of tooth size are in^{-1}. The metric equivalent for diametral pitch is module, a measure of length of the pitch diameter arc per tooth, with units of millimeters. For helical gears transverse module is found using Equation 53, and normal module found using Equation 54. Also, the relationship between the diametral pitch and module is given in Equation 55.

$$\text{Transverse module} = \frac{d}{N} \tag{53}$$

$$\text{Normal module} = \text{transverse module} \times \cos(\text{helix angle}) \tag{54}$$

$$\text{Module} = \frac{25.4}{\text{diametral pitch}} \tag{55}$$

For spur gears, the helix angle is zero and the normal module and diametral pitch are thus equivalent to the transverse ones. The diametral pitches and modules of the pinion gears of interest are given in Table 30.

Table 30 Transverse and Normal Modules and Diametral Pitches

		Transverse		Normal	
	Gear	**Module (mm)**	**Diametral Pitch (1/in.)**	**Module (mm)**	**Diametral Pitch (1/in.)**
Green	Reaction Pinion	1.81	14.07	1.67	15.23
	Input Pinion	1.36	18.67	1.27	20.00
	Output Pinion	1.24	20.53	1.18	21.58
Hard	Rear Short Pinion	1.81	14.03	1.70	14.94
	Rear Long Pinion 1	1.81	14.03	1.70	14.94
	Rear Long Pinion 2				
	Front Short Pinion	1.69	15.03	1.59	15.97

It is seen that for all the pinion gears that pitch diameter ranges from 27.03 mm to 57.78 mm, gear height from 17.40 mm to 35.15 mm, the number of teeth from 16 to 32, normal modules from 1.18 mm to 1.70 mm, and normal diametral pitches from 14.94 in^{-1} to 21.58 in^{-1}. These design values will be used, along with the tolerances specified on the gears, presented next, in an attempt to classify these pinion gears according to the schemes from AGMA and DIN.

7.3.1. Feature Tolerances of the Pinion Gears

The tolerance specifications given in Table 31 detail the accuracy requirements for the pinion gears of interest; units are again in millimeters. It is seen that for nearly all of the feature tolerances specified, that the hard finished pinion gears have stricter tolerance levels, and thus greater precision demands. Definitions of each of the tolerance items follow the table, using some of the gear definitions given in Appendix B, and also (Smith 1992, Dudley 1994).

Table 31 Tolerance Specifications of Pinions of Interest (mm)

<table>
<tr><th>Gear</th><th>Tooth Thickness</th><th>Crown</th><th>Maximum Involute</th><th>Tooth to Tooth Index</th><th>Total Index</th><th>Total Composite Action</th><th>Drive Lead</th><th>Coast Lead</th><th>Measurement Over 2 Balls</th></tr>
<tr><td>Reaction Pinion</td><td>0.0275</td><td>0.0050</td><td rowspan="3">0.0240</td><td rowspan="3">0.0130</td><td rowspan="3">0.0430</td><td rowspan="3">0.0430</td><td rowspan="3">+/- 0.018</td><td rowspan="3">+/- 0.018</td><td>0.0610</td></tr>
<tr><td>Input Pinion</td><td>0.0275</td><td>0.0050</td><td>0.0570</td></tr>
<tr><td>Output Pinion</td><td>0.0275</td><td>0.0050</td><td>0.0595</td></tr>
<tr><td>Rear Short Pinion</td><td>0.0260</td><td>0.0030</td><td rowspan="4">0.0120</td><td rowspan="4">0.0090</td><td rowspan="4">0.0280</td><td rowspan="4">0.0220</td><td>-0.002 / -0.038</td><td>+0.009 / -0.026</td><td>0.0490</td></tr>
<tr><td>Rear Long Pinion 1</td><td rowspan="2">0.0390</td><td>0.0025</td><td>+/- 0.018</td><td>+0.005 / -0.031</td><td rowspan="2">0.0485</td></tr>
<tr><td>Rear Long Pinion 2</td><td>0.0040</td><td>+0.014 / -0.022</td><td>+0.022 / -0.014</td></tr>
<tr><td>Front Short Pinion</td><td>0.0390</td><td>0.0030</td><td>+0.012 / -0.020</td><td>+0.020 / -0.012</td><td>0.0450</td></tr>
</table>

Tooth Thickness – the arc length along the pitch circle across a tooth; tooth thickness tolerances will strongly affect the variation in backlash, which is the gap between mating teeth measured along the pitch circle (Norton 2000). Alternatively, backlash in gears may be defined as the intentional clearance between mating gears; backlash is designed into gears to account for angular misalignment that may result from manufacturing or assembly variation and / or error.

Crown – a modification that causes the center area of a flank of each gear tooth to have a slight outward bulge. A crowned tooth is increasingly thinner toward the ends.

Maximum Involute – the maximum deviation from ideal, theoretical involute profile given on an involute profile diagram, commonly called a “K” chart. The involute profile is the shape of the tooth flank from its root to its tip.

Tooth to Tooth Index – the displacement of any tooth from its theoretical position relative to a datum tooth; also a measure of pitch variation.

Total Index – the maximum difference between the extreme values of index variation for a given gear; it is also equivalent to the total accumulated pitch variation, as measured by a two probe spacing system.

Total Composite Action – also known as runout, it is a measure of eccentricity (i.e., lack of concentricity) relative to the axis of rotations. It is measured in the radial direction and is the amount of difference between the highest and the lowest readings in a full revolution of a gear. Runout is usually checked by rolling a gear with a master gear and recording radial displacement, or by placing a pin in a tooth space and rolling past a dial indicator.

Drive and Coast Lead – the advance in the axial direction of a helical gear for a full revolution as in a screw thread; drive and coast differentiate the sides of the tooth flanks that initiate contact and push into the gear mesh and the opposite side, respectively. This distinction between drive and coast is demonstrated in Figure 84, for a gear with one tooth that rotates in the counter-clockwise direction; if the gear were to be rotated in the clockwise direction, the drive and coast flanks would be switched.

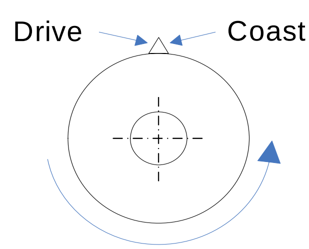


Figure 84 Drive and Coast Flanks of a Gear

Measurement Over 2 Balls – or alternatively, over-pins measurement; pertains to the measurement, radial or diametrical, made across cylindrical pins or balls inserted between the teeth.

According to Dudley, the quality of gear teeth can not be completely controlled until appropriate tolerances are specified on the following items (Dudley 1994): tooth spacing or pitch, tooth profile, concentricity of teeth with axis, tooth alignment, tooth thickness, and surface finish of flank and fillet. The items in Table 31 address these; in Table 32 the tolerance item that addresses those gear features specified by Dudley, required to control gear quality, is given. It is important to understand how these tolerance items are connected to the items described by Dudley.

Table 32 Design Features Controlled by Tolerance Items

Design Feature	Tolerance Item
Tooth Spacing	Tooth to Tooth Index, Total Index
Tooth Profile	Maximum Involute, Crown
Concentricity of Teeth with Axis	Total Composite Action, Measurement Over 2 Balls
Tooth Alignment	Drive and Coast Lead
Tooth Thickness	Tooth Thickness
Surface Finish of Flank	(not specified)

Fixing these tolerances specifies the accuracy and precision, and thus the quality, of a gear. Using the pitch diameters, modules, and diametral pitches of Tables 29 and 30, and the tolerances specified for the gears in Table 31, the pinion gears may be classified according to the AGMA and DIN standards in Appendix B. For both standard classifications, the tolerances items of Table 31 do not match the standards' tolerance items exactly. The values for total composite action are used for runout, tooth-to-tooth index is used for pitch tolerance and tooth-to-tooth spacing, total index is used cumulative spacing, and maximum involute is used for profile tolerance. Using these tolerance items, the pinion gear designs are classified; accuracy limits are given for ranges of diametral pitches and pitch diameter for each tolerance item. Using the charts in Appendix B, the pinion gears of interest may be classified in the Quality ranges given in Table 33.

Table 33 AGMA and DIN Quality Classifications of Pinion Gears

<table>
<tr><th></th><th>Gear</th><th>AGMA</th><th>DIN</th></tr>
<tr><td rowspan="3">Green</td><td>Reaction Pinion</td><td rowspan="3">≤ 9</td><td rowspan="3">5 - 7</td></tr>
<tr><td>Input Pinion</td></tr>
<tr><td>Output Pinion</td></tr>
<tr><td rowspan="4">Hard</td><td>Rear Short Pinion</td><td rowspan="4">9 - 11</td><td rowspan="4">4 - 5</td></tr>
<tr><td>Rear Long Pinion 1</td></tr>
<tr><td>Rear Long Pinion 2</td></tr>
<tr><td>Front Short Pinion</td></tr>
</table>

The hard finished gears, with their tighter tolerance requirements seen in Table 31 indeed have quality number indicative of these tighter tolerances. Ranges are given instead of single numbers due to the ranges for gear sizes (i.e., diametral pitch and pitch diameter) given in the standards, and the specification for tolerance items falling in different quality grades. In this situation, the more accurate quality grade should be selected; however, it is seen here that the quality grade classifications do not provide the necessary fidelity for specifying gear tolerances optimally. Also, these specific pinion gear designs do not fit neatly into the standard classification size ranges, a fact which makes quality assignment and classification difficult and somewhat uncertain. Given these difficulties, transmission gear designers do not use the quality grades when specifying the precision of their gears; quality grades are useful however in certain contexts such as process planning, cost estimation, and quoting.

Clearly the design of a gear with its complex geometries and many design objectives is not a trivial exercise. Additionally, specifying the many tolerances which control the precision of gearing and then successfully manufacturing them is also a substantial challenge. Discussed previously, process planning is the vital link between product design and manufacture, and it is no less so in transmission gear design and manufacture. In process planning, it is not immediately clearly which of the gear tolerances are the most significant. AGMA and DIN define gear quality levels by multiple feature tolerances, and not a single feature, so it may follow that process planning for manufacturing a gear design must simultaneously consider more than one design feature at a time, as the individual processing steps do not affect individual gear features in isolation. Experience working with industry leads to the conclusion that gear process planning is a finely honed art attributable to significant expertise and experience of manufacturing engineers and process planners. The specifics of process planning for transmission gearing is beyond the scope of this thesis; for the purposes here, it suffices that the pinion gears from the two transmissions are of different quality levels with differing feature tolerance requirements, thus necessitating different manufacturing processes. Before applying the tool developed in this thesis to estimate the environmental and cost performances of those different manufacturing processes, an overview of gear processing methods is presented in the next section.

7.4 Overview of Gear Processing

It has been discussed how important gear feature tolerances are in terms of their impacts on potential gear noise in operation, a critical concern for automobiles and their perceived quality, and thus vehicle salability. According to AGMA, the realistic quality of manufacturing determines the noise generated by gearing (AGMA 2004); successfully producing these complex components is not easy. In Figure 85, an overview of the many different means of creating gears is given, adapted from Dubbel, et al. (Dubbel, et al. 1994).

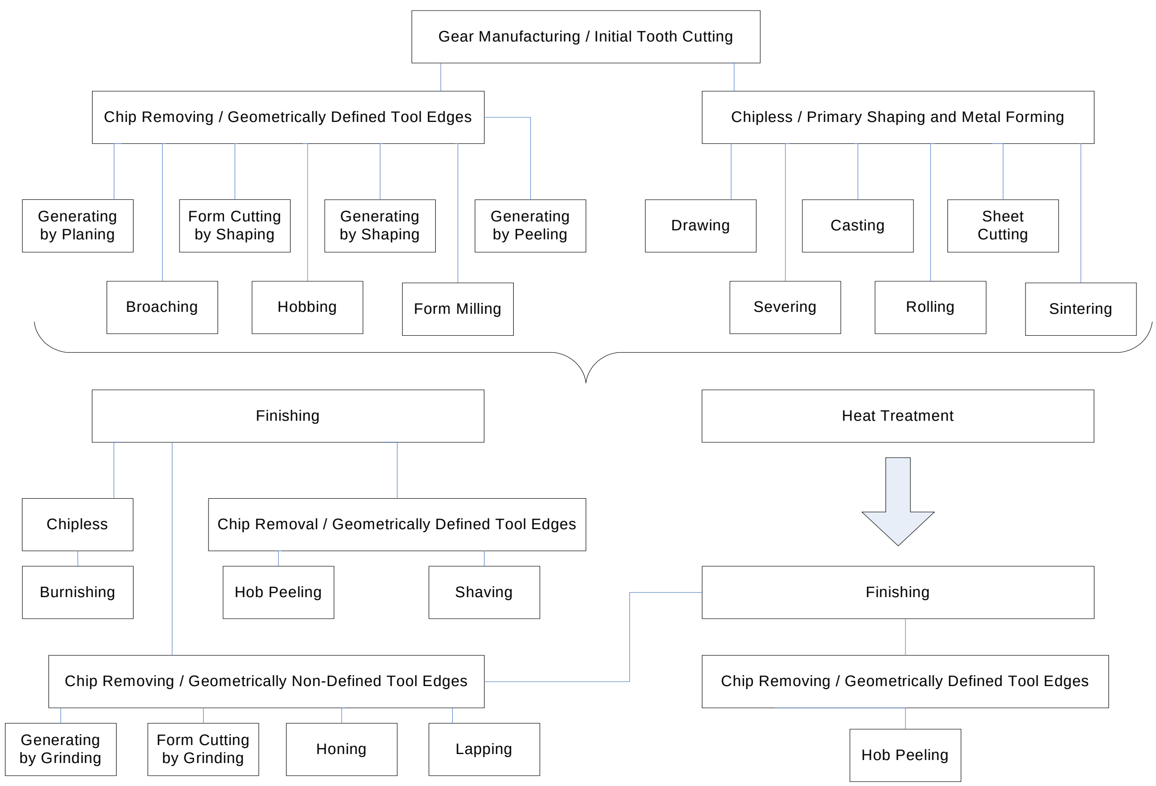


Figure 85 Different Gear Manufacturing Processes, from (Dubbel, et al. 1994)

Many different ‘paths’ may be taken in Figure 85 to achieve a fully realized, production gear. Generally, these paths must follow these general operations: create teeth and finish teeth. Both operations may be achieved by numerous means; creating teeth may be done by cutting the teeth and removing metal, or by shaping the teeth by forming them. Finishing may be done prior to, or after heat treatment hardening, if it is required for hardening the gear material for sufficiently long life and other performance requirements. For automatic transmission gearing, given their specific design requirements, the following high level operating steps are performed, and the specific instances of the methods to achieve the high level operation studied in this case study are given.

1. **Cut teeth –** Solid cylindrical blanks are the starting point of the process; teeth are formed by cutting the blanks. Cutting may be performed by a number of means, but here dry hobbing is employed. Hobbing is a common gear cutting operation used in many high volume applications. Dry operation entails an absence of metal working fluid, and offers cost and environmental benefits to a manufacturer.
2. **Green Finish teeth –** After having its teeth cut, a gear may be green finished to remove or correct any errors introduced in the teeth cutting operation. This is accomplished here by (cold) rolling.
3. **Harden teeth –** To increase durability and performance over a sufficiently long use phase of the life cycle, transmission gears are typically hardened. Hardening, accomplished by carburizing processes, is most often done using heat treatment furnaces. In elevated temperatures, carbon is more readily absorbed by the high carbon steel gear material, providing a degree of case-hardening to a depth

determined by the heat treat process parameters. Carburizing may also be accomplished in a low-pressure, near vacuum environment; the decreased pressure levels cause carbon to again be absorbed, but at much faster rates, allowing for same resulting case-hardness in lesser time. The most serious side effect of this necessary hardening is the introduction of defects into the gears by heat induced distortion and / or warping.

4. **Hard finish teeth** – Explained previously, hard finishing is the correction of errors resulting from the hardening of the gears. Since the gears have been hardened, removing metal is now more difficult, which entails greater costs to the manufacturer. Hard finishing is achieved here through grinding and honing of the teeth profiles. Grinding corrects distortion or warping due to heat treatment and also improves surface finish quality. Honing is a finer version of grinding that does not remove as much material, and is used to achieve very, very smooth surfaces finishes and feature tolerances.

Each of these operations, and their numerous auxiliary, support operations, have inputs and outputs, beside the production gears during their operation. Known inputs include liquid coolant used as metal working fluid, water, compressed air, machine tooling, and electricity, among others. Known outputs include spent machine tooling, grinding swarf, machine chips, spent coolant and oils, among others.

With respect to cost and environmental performances in gear manufacture, it is desired to minimize the financial costs, environmental burdens, and the environmental impact of the materials and energy required to convert transmission pinion gears from blanks to finished gears, ready for assembly into the transmission. The inputs to and the outputs from gear manufacture are depicted in Figure 86.

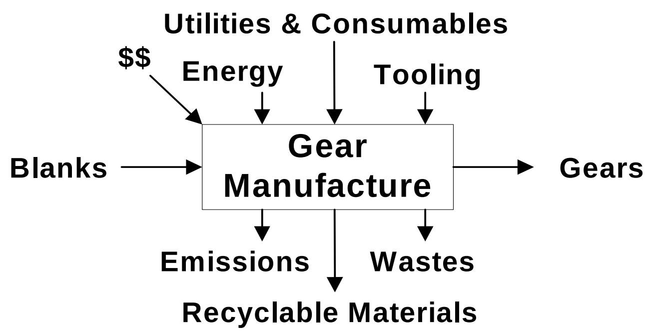


Figure 86 Inputs and Outputs to Gear Manufacture

Energy is typically in the form of electricity, compressed air, and combustible gases; utilities and consumables include water, other process gases, filters, and fluids; tooling is that which is used to directly create the gears and is commonly consumed or spent in the part creation process; the emissions considered are CO_2 indirectly attributable through the use electricity generated in a power plant by various methods; wastes are those materials sent to landfill or that require special handling and handling due to their hazardous nature (e.g., grinding swarf and sludge); and recyclable materials are those which may be sold by the manufacturer and used as the source of material content for other parts. To gauge the performance of the gear manufacture, these items need to be quantified for each operation step in the process, and the financial costs and environmental impacts tallied.

7.4.1. Costs of Gear Processing

The relative financial costs of producing different quality levels of gears are fairly well understood. The general trend for the costs to produce gears of different AGMA and DIN quality levels is given in Figure 87, taken from (Dudley 1994). It is seen that the relative costs of producing gears with increasing tolerance requirements also follows the exponential shape like the one seen previously in Figure 3 of Chapter 2. The x-axis in Figure 87 are the quality numbers defined by AGMA and DIN; as AGMA quality numbers increase, and DIN quality grades decrease, tolerances on gear features decrease (i.e., become tighter). Remembering Table 33, the green finished pinion gears could be assigned quality numbers of 9 and 7 from AGMA and DIN, respectively, and the hard finished pinion gears could be assigned quality numbers of 11 and 4 from AGMA and DIN, respectively. Ranges were given in Table 33, but from this point forward the different pinion gears are assigned these fixed Quality numbers. Based on the curves of Figure 87, with the quality numbers for the green finished and hard finished gears plotted, estimates for the relative cost of producing the gears may be ascertained. These relative estimates may be compared to the relative differences of the cost estimates generated by the method proposed in this thesis to serve as partial validation by verifying that the relative cost differences are the same magnitude as what is expected, generally, in common gear manufacturing.

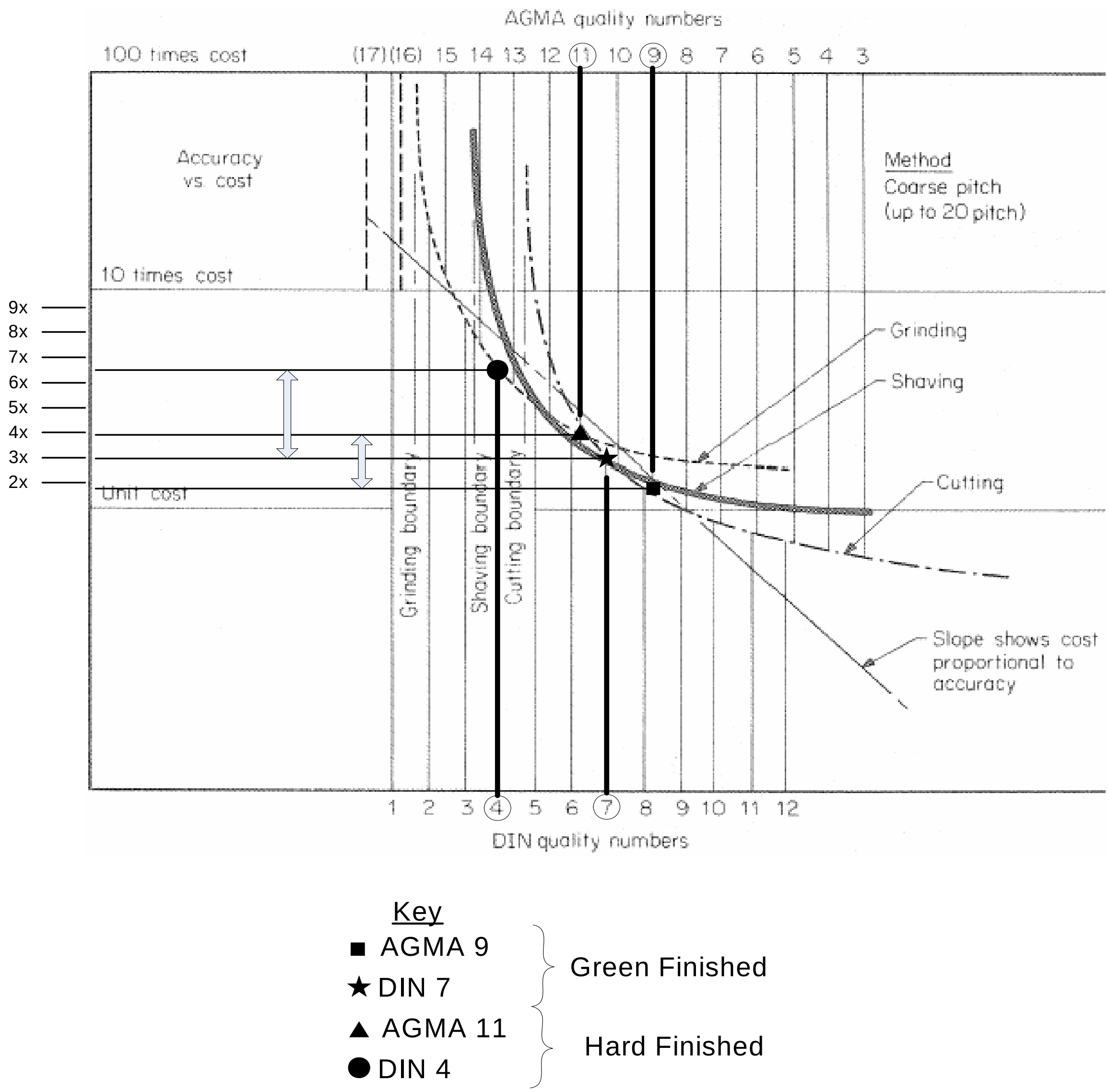


Figure 87 General Trend of the Cost of Making Gear Teeth (Dudley 1994)

In Figure 87, the green finished points are plotted on the curve for ‘cutting’, while the hard finished points are plotted on the curve for ‘grinding’, since these pinions are produced and finished by these methods predominantly. To estimate the relative differences in costs, the multiple of unit cost for each quality assignment is read off the y-axis of Figure 87. These multiples are recorded in Table 34.

Table 34 Multiples of Unit Cost to Produce Pinion Gears

	Quality Classification	Multiple of Unit Cost
Green	AGMA 9	2
	DIN 7	3
Hard	AGMA 11	4
	DIN 4	6.5

Using the multiples given in Table 34, the relative cost differences, as predicted by both AGMA and DIN quality classifications, may be found by dividing the larger multiple by the smaller; here this is essentially dividing the hard finished multiple of unit cost by the green finished multiple. The relative differences for each classification scheme are depicted in Figure 87 by the vertical, double headed arrows. The relative cost difference, per each classification scheme, predicted between green and hard finished pinions is shown in Table 35; both means predict an approximately two-fold increase in cost for producing the hard finished pinion gears over the green finished gears.

Table 35 Relative Cost Difference for Green and Hard Finished Pinions

	Relative Cost Difference
AGMA	2.00
DIN	2.17

This prediction of course is approximate, and the quality classification numbers have been used as a proxy to or abstraction of the actual pinion gear tolerance designs, and the cost curves of Figure 87 are general gear production costs compiled by industry-wide surveying not constrained to specific gearing applications, such as automotive transmissions. Despite this approximation and uncertainty, this relative cost difference will be an interesting metric by which to gauge estimates for costs only, from the method developed in this thesis.

To achieve the high accuracy of higher quality gears, which increases the manufacturing costs, several important variables to be controlled and addressed are given by Dudley (Dudley 1994): machine operator skill, blank accuracy, material, and heat treatment, cutting or grinding tool accuracy, mounting of cutting tool or grinding wheel, work-holding fixture accuracy, accuracy in mounting of work-holding fixture, production method, distortion, and inherent capability and condition of machine tool. These items, specific to gear production, are highly in agreement with the more generalized factors for controlling manufacturing processes discussed earlier in Chapter 2.

With the design and manufacture of the various system levels of an automobile, from the vehicle itself down to the component level of a transmission gears, and their impacts on cost and environmental performances discussed, and greater detail on the specifics of gear design and manufacture, as it relates to noise performance and costs all given, the method proposed in this thesis is employed to analyze the cost and environmental performances of the two methods to produce the different transmission pinion gears.

7.5.Assumptions and Inputs

Before generating the manufacturing performance estimates, input parameters and assumptions are spelled out, as similarly done for the illustrative examples of the previous chapter. The inputs required are cost rates and eco-indicators, facility parameters, and the databases for both primary and auxiliary machinery required for high volume gear manufacture. The uncertain cost rates are given in Table 36 with lower and upper bounds on their uniform distribution; these values are the same as for the illustrative examples. The same Eco-indicator 99 values are used as in the illustrative examples and are not repeated. The facility parameters are known and are given in Table 37. The number of operators for the pinion lines is a non-integer reflecting the sharing of an operator between other gear production lines.

Table 36 Uncertain Cost Rate Input Parameters

Costs	LB	UB	Units
Operator Labor	40.00	60.00	$/hr
Electrical Energy	0.020	0.060	$/kWh
Compressed Air	0.010	0.030	$/cf
Water	0.00150	0.00331	$/gal
Regular Landfilling	25.00	50.00	$/ton
Recycling	-300.00	-200.00	$/ton
Special Wastes	65.00	90.00	$/ton

Table 37 Known Facility Input Parameters

Facility Parameters	Value
Shifts / Week	15
Hours / Day	24
Days / Week	5
Weeks / Year	47
No. Operators	2.1
Years to Depreciate	10

7.5.1. Machinery Databases

Discussed in Chapter 4, the machinery databases are perhaps the most important aspect of the method proposed in this thesis. Incorrect data and information in the machine databases will cause the best performance estimation models to yield inaccurate outputs. Data in the machine databases is for a number of real gear processing machines to be used in the production of the pinion gears, among other gear production lines, for their respective transmissions. The machines on which data has been collected, and are available for use in the production lines, are given in Figure 88 below; any combination of these machines may be assembled and the aggregate cost and environmental performances of that proposed production line may be estimated.

Primary	Auxiliary
Dry Hob	Dust Collector
Chamfer	Mist Collector
Roller	Coolant System
Pre-HT Washer	Chiller
HT Furnace	Material Handler
Face Grinder	External Loader
Bore Hone	
Pre-Grind Washer	
Burnisher	
Teeth Grinder	
Final Washer	

Figure 88 Available Gear Processing Machines

The data on these machines was collected from a number of sources: machine vendor documentation, submitted energy and environmental checklists required as part of the new machine qualification process and typically filled out by the machine vendors, manufacturing engineers responsible for the machines in the plant facility, and internal energy studies conducted on machine energy usages. Presented in this thesis and for publication, environmental burden rates and machine costs (i.e., acquisition, tooling, and consumables) for primary and auxiliary machines, where applicable, have been intentionally altered by a factor. Batch sizes and processing times are still representative of the actual machine operations, and cost rates are general for any industrial facility in the US.

This environmental data and information on these gear processing machines (primary and auxiliary) does not exist in a central location; many different and wide ranging sources were examined in an attempt to distill this information into what is presented. Even with all the data gathering there are gaps in these databases, and uncertainty about the true values for machine operating characteristics. More often than not, vendor supplied data on the environmental performance of their machines is not correct; at worst this information is supplied merely as a formality with no regard to accuracy, and at best the values are determined at the vendor's facility for more general machine operation and is most likely not reflective of the machine's operation in the manufacturer's facility.

Both transmission programs were in their early stages of rollout and neither of the gearing production lines was operating at steady state, full production volumes. Thus, not much historical information existed for machine operations, and pre-production values were used. Given the lack of historical, empirical data to characterize machine operation, and the fairly high degree of uncertainty associated with machine data due to the conflicting or widely varying values ascertained from the various data sources, the use of uniform distributions were used to model uncertainty. The use of uniform distributions is indicative of a high degree of uncertainty for model input parameters where little, or imprecise knowledge exists; lower and upper bounds of the parameter are set, but no idea of the relative likelihood within those bounds is known. When historical or steady state information exists, another distribution, such as normal or some other empirical fit, may be employed to model not the epistemic uncertainty, but the aleatory uncertainty, also known as the variability, which is inherent in manufacturing operations.

Given the gaps present in the database, any performance estimates resulting from the use of the proposed method must be considered as preliminary. This is especially true for the auxiliary machinery; scarce information on the environmental performances of the auxiliary machinery is known. These many blanks and gaps in both databases could have significant effects on estimates. As additional information is added and the uncertainty of the machine operating characteristics reduced, the performance estimates and ensuing conclusions possibly may change, but the confidence in those estimates may be increased. The estimates are perhaps not as meaningful as stand alone estimates at this preliminary stage, but when making comparisons with alternatives, whose performance estimates are generated with this same incomplete database, the errors and gaps may be considered as common and subtracted out.

The machinery databases are presented on the next two pages; primary machines in Table 38, and auxiliary machines in Table 39.

Table 38 Primary Machine DB

		Dry Hob		Chamfer		Roller		Pre-HT Washer		HT Furnace		Face Grinder	
Characteristic	Units	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
Electrical Power	kW	3.329	8.463	2.088	6.770	3.385		43.838		388.727	789.865	6.093	25.163
Compressed Air	cfm	5.642		1.128	3.761							0.021	0.474
Water Use	gph	0.000		0.000				2.821		1128.379		45.135	
Landfillable Waste	lb / hr					0.001							
Recyclable Material	lb / hr	19.182		0.275									
Special Waste	lb / hr											0.110	
Batch Size	--	1		1		1		928		928		1	3
Processing Time	min	0.200	0.392	0.268	0.333	0.117	0.167	32.000		180.000		0.067	0.250
Yearly Tooling	$	36052		101554		169						3047	
Yearly Consumables	$	282		564		282		282		282		564	
Acquisition	$	19916		93655		287172		141047		304662		295071	

		Bore Hone		Pre-Grind Washer		Burnisher		Teeth Grinder		Final Washer	
Characteristic	Units	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
Electrical Power	kW	13.541	103.811	9.478	45.135			7.165	22.850	27.645	72.865
Compressed Air	cfm	18.336	33.851	0.564	22.568	7.436		0.993	2.257	0.564	2.257
Water Use	gph	4.514	846.284	0.303				0.001	3.047	0.564	11.284
Landfillable Waste	lb / hr					0.001					
Recyclable Material	lb / hr										
Special Waste	lb / hr	0.015		0.056				7.126			
Batch Size	--	4	10	1		1		1		1	40
Processing Time	min	0.133	0.706	0.073	0.550	0.071		0.742	0.815	0.150	0.927
Yearly Tooling	$	20311				169		56137			
Yearly Consumables	$	1128		1128		282		846		1128	
Acquisition	$	311997		52470		116223		677028		141047	

Table 39 Auxiliary Machine DB

		Dust Collector		Mist Collector		Coolant System		Chiller		Material Handler		External Loader	
Characteristic	**Units**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**
Electrical Power	kW	8.841	15.730	11.340	244.125	23.640		4.231	153.911	2.234	3.921	2.234	5.078
Compressed Air	cfm	0.293	7.052							5.642		0.564	
Water Use	gph	0.000											
Landfillable Waste	lb / hr												
Recyclable Material	lb / hr												
Special Waste	lb / hr												
Yearly Consumables	$	2821		9027		1128		564		282		282	
Acquisition	$	63302		66856		543315		11284		84628		84628	

Process capability information of individual machines, which is another critical component of the primary machine database, per the proposed method, is proprietary and is not discussed or presented here. If this process capability information were available however, it may be entered into the tool and used to assist in basic process planning. Process planning is not conducted in this study, rather the known manufacturing processes already in place to produce these different gear designs is examined and the tool used to perform an assessment of likely manufacturing performances.

7.5.2. Assumptions

A number of assumptions were made to create an inventory of environmental burdens, and estimate the costs and environmental impacts for the process proposed to manufacture gears.

- The annual number of transmissions of each type to be produced per year is 450,000. The number of pinion gears per year are therefore 450,000 multiplied by the number of the pinion gear per transmission.
- The waste stream of by-products is made up of landfillable wastes, recyclable materials, and special, or hazardous, wastes that require alternative disposal methods; within each waste stream category, the content is *homogeneous*;
- Metal chips from dry operations are considered to be wholly recyclable;
- Sludge and swarf wastes from grinding and honing operations are special wastes;
- Similarly to the illustrative examples, the production line is up and running; that is, in steady state operation. Start up, shut down, and preventive maintenance procedures are not included, but their impacts on costs and the environment could be significant

(e.g., flushing of fluids from washers and coolant systems, or turning on / warming up a heat treat furnace).

7.6.Green Finished Pinion Gears

The pinion gears which are green finished, and the FWD transaxle into which they are assembled, have previously been introduced. The pinion gears are in simple planetary configurations in the transmission. In addition to the gearing necessary for the planetary configurations (i.e., sun and ring gears in addition to the pinions), the transaxle contains the final drive gearing, that in a RWD vehicle is a separate entity from the transmission. A listing of all the gears in the 6 speed FWD transaxle, along with their quantities in the transmission, is giving in Table 40.

Table 40 Gears in 6 Speed FWD Transaxle

Name	Qty per Trans
Input Pinion	4
Reaction Pinion	3
Output Pinion	5
Input Sun	1
Reaction Sun	1
Output Sun	1
Input Ring	1
Reaction Ring	1
Output Ring	1
Front Transfer Drive	1
Transfer Driven	1
Final Drive Pinion	1
Final Drive Ring	1

Other than the pinion gears, there is only one of each gear per transmission and their annual production volume is the same as that of the transmission itself, here assumed to be 450,000 transmission per year. The annual quantities required of the pinion gears are multiples of the transmission quantity; they are listed in Table 41. The annual quantities of the gears, and the pinion gears specifically here, along with the working hours per year, are used to determine the hourly production rate for a production line. Line dynamics such as uptime, defect fall out rates, and utilization are not explicitly considered; hourly production rate is the number of finished, produced gears required in a working hour to meet the required annual volume, assuming equal distribution of the production over an entire working year.

Table 41 Green Finished Pinion Annual Quantities

Name	Qty per Trans	Annual Qty
Input Pinion	4	1800000
Reaction Pinion	3	1350000
Output Pinion	5	2250000

The green finish process used to manufacture the pinion gears is presented pictorially in Figure 89; each of the three green finished pinions have their own production line. That is, the process flow of Figure 89 is replicated three times, and there is no change-over on a line in order to produce different parts on one line. Not pictured in Figure 89 is the auxiliary machinery which supports the primary process flow. These auxiliary machines include dust and mist collectors on the cutting operations, a coolant system for the cutting operations, and material handling equipment between each of the primary processing steps and at the beginning and end of the process flow. The full list of machines used in the green finishing process, including the auxiliary machinery not pictured in Figure 89, is given in Figure 90.

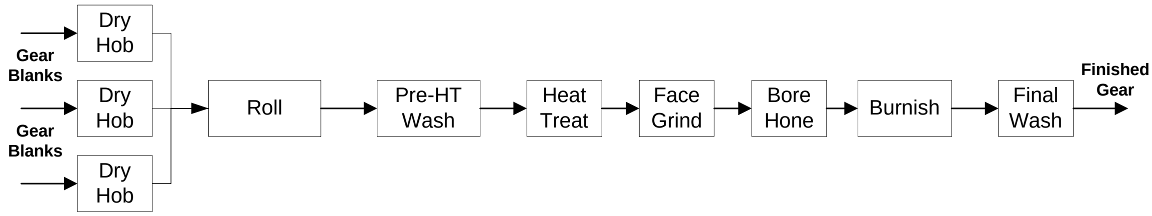


Figure 89 Green Finished Pinion Process Flow

Primary Machines	Auxiliary Machines
Dry Hob	Dust Collector
Roller	Mist Collector
Pre-HT Washer	Coolant System
HT Furnace	Material Handler
Face Grinder	External Loader
Bore Hone	
Burnisher	
Final Washer	

Figure 90 Green Finished Pinion Process Machines

With the machines in the process spelled out, the tool developed to instantiate the proposed method may be employed. The listing of gear processing machines in Figure 90 are selected in the front end process generation portion of the developed tool; this selection is accomplished simply by choosing each machine in the green finishing process from a listing of the available gear processing machines. These selected machines have their associated operating characteristic data extracted from the databases and are exported to the back end process accounting portion of the developed tool. The operating characteristic data imported into the back end feeds the mathematical models previously explained to generate estimates on the amounts of environmental burdens generated by the proposed process. Machine costs and labor costs are also calculated, and the environmental burdens used to determine the environmental impacts and single point environmental impact score, as well as the costs associated with utilities purchase and by-products disposition. To improve the accuracy of these estimates the steps discussed previously should be employed; specifically, the number of machines and hourly production rates supported by auxiliary machines should be updated to reflect the actual manufacturing process. In the case of early product design, this information is not likely known well, but since this analysis is of existing gear production lines, the numbers of machines and hourly production rates may be determined using the methods introduced in Chapter 3.

7.6.1. Number of Machines and Hourly Production Rates

When there is no sharing of machines between production lines determining the number of each machine and the hourly production rates of the auxiliary machinery is simple. However, the production of these pinion gears for the FWD transaxle does not take place in isolation; not only are primary and auxiliary machines shared among the pinion gear lines, they are shared among the production lines for all of the gearing in the transmission. Therefore to properly attribute machine performance to the pinion gear of interest, the fractions of primary and auxiliary machine use for that pinion gear must be determined. The shared primary and auxiliary machinery present on the green finishing gearing processes, and their quantity, are given in Table 42. These machines are not simply shared among the three pinion gear production lines; they are also used to support the production of all the gearing of the transmission. It should be noted that one final washer is shared by the reaction and input pinion lines; the sharing by other gear lines of other final washers is unknown, and thus the assumption is made that other gear production lines share one other final washer.

Table 42 Shared Machinery on FWD Transaxle Gearing Processes

Shared Primary Machinery		Shared Auxiliary Machinery	
Pre-HT Washer	1	Dust Collector	1
HT Furnace	4	Mist Collector	1
Final Washer	2	Coolant System	1

To determine the machine fractions for primary and auxiliary machines requires the use of Equation 7 for primary machine fractions, and Equations 15, 16, and 17 for auxiliary machine fractions, developed in Chapter 3. These equations are to be used because the differing production rates of the different gears causes unequal sharing of the machinery. Using the knowledge of the total numbers of gear primary machinery, production rates for each gear, and the primary operations which are supported by particular auxiliary machinery, the machine fractions may be computed. The number of machines and the support of primary machines by auxiliary for the FWD transaxle are presented in Appendix C, including the machine fractions for all the gear production lines. The production rates for each gear may be determined using the assumed volume of transmissions in a year and the number of gears per transmission. Using this information and the Equations above, the machine fractions may be calculated; for the green finished pinion gears the number and fractions of machines is given in Table 43.

Table 43 Number and Fractions for Green Finished Pinion Process Machines

	Pinion:	Reaction	Input	Output
Primary	Dry Hob	3		
	Roll	1		
	Pre-HT Washer	0.136	0.182	0.227
	HT Furnace	0.545	0.727	0.909
	Face Grinder	1		
	Bore Hone	1		
	Burnisher	1		
	Final Washer	0.429	0.571	0.333
Auxiliary	Dust Collector	0.170	0.226	0.283
	Mist Collector	0.106	0.141	0.176
	Coolant System	0.106	0.141	0.176
	Material Handler	7		
	External Loader	2		

To determine hourly production rates of the auxiliary support machinery Equations 18, 19, and 20 from Chapter 3 may be used. These equations are to be used because the differing production rates of the different gears causes unequal sharing of the machinery. Using the same information as required to calculate machine fractions for sharing (i.e., number and types of machines supported and productions rates), the auxiliary production rates may be found; these auxiliary production rates are presented in Tables 44 and 45. In Table 44 the hourly production rates of all the gear lines are also given for reference. Table 45 contains those auxiliary hourly production rates that are dependent on the production rates of the pinion gears, which differ due to the different numbers required in the transmission. These auxiliary machines in Table 45, the material handling equipment, interact with the production gears directly, and thus the hourly production rate that they support, is the hourly production rate of the line itself.

Table 44 Hourly Production Rates

Hourly Production Rates	
Dust Collector	1520
Mist Collector	4960
Coolant System	4960
Input Pinion Line	320
Reaction Pinion Line	240
Output Pinion Line	400
Other Gear Lines	80

Table 45 Pinion Dependent Hourly Production Rates

Pinion:	Reaction	Input	Output
Material Handler	240	320	400
External Loader	240	320	400

With the types and numbers of machines, and the auxiliary hourly production rates, specified, the developed tool is employed to generate estimates for the cost and environmental performances of this manufacturing process for the green finished transmission pinion gears.

7.6.2. Manufacturing Performance Estimates for Green Finished Pinions

To use the tool to generate the manufacturing performance estimates, the following general steps are followed: (1) the primary and auxiliary machinery is selected from the list of available gear processing machinery, (2) machine data and information is pulled from the respective database, (3) the numbers of machines, machine fractions, and auxiliary hourly production rates supported are inputted to reflect the actual manufacturing process, (4) mathematical models are applied to estimate the quantities of environmental burdens, (5) environmental burdens are converted to financial costs and environmental impacts, (6) all costs and environmental impacts are summed to yield single point cost and environmental impact score, which along with the inventory of environmental burdens constitutes the indicators of manufacturing performance, and (7) uncertainty analysis is conducted using Monte Carlo simulation. This procedure was followed for each of the three green finished pinion gears of the FWD Transaxle; their manufacturing performance estimates are presented in Tables 46, 47, and 48. The per-gear results of the uncertainty analysis are presented, with the mean (μ), standard deviation (σ), minimum, and maximum, along with the units for each indicator.

Table 46 Reaction Pinion Environmental and Cost Performance Estimates

	μ	**σ**	**Min**	**Max**	**Units**
Environmental SPS	153	11.3	124	187	mpt / part
Financial Cost	1.11	0.117	0.84	1.46	$ / part
Water Use	2.5	0.37	2.0	4.1	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.28	0.053	0.19	0.38	lb / part
Special Waste	0.00	0.000	0.00	0.00	lb / part
Energy	5.0	0.38	4.1	6.2	kWh / part
CO2	6.72	0.502	5.46	8.27	lb / part

Table 47 Input Pinion Environmental and Cost Performance Estimates

	μ	**σ**	**Min**	**Max**	**Units**
Environmental SPS	146	12.5	113	186	mpt / part
Financial Cost	0.89	0.101	0.65	1.19	$ / part
Water Use	3.2	0.36	2.7	4.8	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.28	0.053	0.19	0.38	lb / part
Special Waste	0.00	0.000	0.00	0.00	lb / part
Energy	4.8	0.41	3.7	6.1	kWh / part
CO2	6.44	0.553	4.97	8.18	lb / part

Table 48 Output Pinion Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	146	13.6	114	191	mpt / part
Financial Cost	0.77	0.091	0.57	1.02	$ / part
Water Use	3.8	0.37	3.3	5.6	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.28	0.053	0.19	0.38	lb / part
Special Waste	0.00	0.000	0.00	0.00	lb / part
Energy	4.8	0.45	3.8	6.2	kWh / part
CO2	6.45	0.596	5.02	8.34	lb / part

The Monte Carlo simulations iterated hundreds of times in each analysis. Given the uncertainty of machine information in the databases, knowledge of the resulting uncertainty in performance estimates is critical. As a caveat, the lack of information for some items in the machine databases must be factored in to decision making; an estimate of zero for an indicator does not necessarily mean that there is zero of that item. The three green fished pinion gears all have similar designs, and thus the similarity in manufacturing performances is expected. Using the deterministic results from the tool, a comparison of the three gears' performances in their manufacture is given in Table 49.

Table 49 Comparison of Green Finished Pinion Process Environmental and Cost Performance Estimates

		Reaction Pinion	Input Pinion	Output Pinion	units
Main	Environmental SPS	151	145	145	mpt / part
	Financial Cost	1.10	0.89	0.76	$ / part
Inventory	Water Use	2.5	3.1	3.8	gal / part
	Landfill Waste	0.00	0.00	0.00	lb / part
	Recyclable Material	0.28	0.28	0.28	lb / part
	Special Waste	0.00	0.00	0.00	lb / part
	Energy	5.0	4.8	4.8	kWh / part
	CO2	6.66	6.38	6.39	lb / part

The interesting things to note in Table 49 are the differences in environmental single point score, financial cost, water use, and energy and CO_2; also, recyclable material is constant. These differences may be attributed to the differing quantities of each gear produced; the quantity of gear per transmission increases from left to right in the table: three reaction pinions, four input pinions, and five output pinions. The increased quantities will have a lower per-gear cost and environmental impact score, because the cost and environmental burdens / impacts are spread over more functional units. Energy exhibits the same behavior, as does CO2 because it is calculated directly from energy use, primarily electrical energy used both directly and indirectly in producing compressed air. Water use increases however with increasing gear quantities, perhaps due to the additional water needed in cleaning operations. Recyclable material generation remains constant, due to the relative sameness of the pinion blank and gear designs. The estimates of zero for both landfill waste and special waste for all of the green finished pinion gears is suspect. The amount per gear is miniscule, and does not show up with three decimal places, and the landfill and special waste generation rates are not adequately known for the machinery in these processes. This warrants further investigation to ascertain the actual operating behavior / characteristics of these machines; particularly the dust and mist collectors since they are clearly known to collect by-products from machine operations.

Averaging the manufacturing performance of the three green finished pinion gears, yields a somewhat representative picture of green finished pinion gear manufacture, with an AGMA Quality number of 9. The averages of the deterministic tool estimates, as well the estimates from the uncertainty analyses, are given in Table 50.

Per statistical arithmetic, to find the standard deviation of the average mean required averaging the standard deviations of the three pinion gears, and then dividing by the square root of 3.

Table 50 Average Green Finished Gear Process Environmental and Cost Performance Estimates

			MC Output		
		Tool Output	μ	σ	units
Main	Environmental SPS	147	148	7.2	mpt / part
Main	Financial Cost	0.92	0.92	0.059	$ / part
Inventory	Water Use	3.1	3.2	0.211	gal / part
Inventory	Landfill Waste	0.00	0.00	0.000	lb / part
Inventory	Recyclable Material	0.28	0.28	0.031	lb / part
Inventory	Special Waste	0.00	0.00	0.000	lb / part
Inventory	Energy	4.9	4.9	0.238	kWh / part
Inventory	CO2	6.48	6.54	0.318	lb / part

Again a comparison of the deterministic performance estimates may be made to those performance estimates generated using Monte Carlo simulations. The mean of the performance estimates and the deterministic results are quite similar. However, the probabilistic results from the Monte Carlo analysis provide better decision support by also including the uncertainty in the performance estimates by giving the spread of the performance estimates. This is the primary benefit of using Monte Carlo simulation in conducting uncertainty analysis, which better supports rational decision making by giving insight into the risks associated with making decisions based on these estimates.

7.6.2.1. A Parametric Study of Green Finishing Performances

The operation and performance of the green finished gear processes to produce the specific pinions for the 6-speed FWD transaxle has been discussed. These green finished pinion gears may be generally characterized by an AGMA Quality number classification of 9; this Quality number is a measure of the tolerance specifications of various features of the designed pinion gears. The green finishing processes have been designed and implemented for the production of these particular pinion gears, but it is expected that for the green finishing process some range in gear feature tolerances may be achieved, depending on the particular operation of the machines in the process.

Similar to the parametric studies conducted in Chapter 3 to understand the behavior of the environmental burden models as a function of feature tolerances, the manufacturing performance behavior of the green finishing process selected and implemented to produce AGMA Quality classification 9 pinion gears, as a function of the gear feature tolerances, will be examined here. According to the Machinability Data Center, for gears with AGMA quality numbers of 9 and above, it is recommended that typical feed rates be reduced by 50% and multiple cutting passes made (MDC 1980). Clearly reducing feed rates or increasing the number of cutting passes in an operation will increase the processing time of a given operation, and increase estimates of manufacturing performance.

The specific tolerance limits of the green finishing process for pinion gears are not known; however, using the MDC recommendation that feed rates be reduced by 50% for increasing gear quality number (per AGMA) and thus tightening the gear feature tolerances, multiples of the typical processing time at the tolerance limit and the tolerance upper bound may be set. An assumption is made that the characterization of the specific green finishing process for these pinions gears is of the typical operation; thus the production of AGMA Quality number 9 pinion gears may be considered the mid-point within the process gear feature tolerance capability spectrum. In reality however, simply assigning an AGMA Quality number does not have the necessary fidelity to adequately specify all the gear feature tolerances required, and the location of these pinion gears in the green finishing process's gear feature tolerance capability spectrum is unknown. For the sake of discussion here however the pinions will be assumed to be located squarely in the middle of this tolerance capability range, as the 'typical' tolerance achieved by the process. Using the known green finishing process whose operation information is housed in machine databases, manufacturing performance estimates for other gears produced via this process with different feature tolerance requirements, though still within the process capability, may be generated.

In Figure 91 a 2^{nd} order and a linear relationship relating feature tolerance level of the gear production process to multiple of the typical processing time are given. The typical processing time is that to achieve the typical tolerance on a production gear from the line, and is here assumed the known processing times of the machinery used to produce the AGMA Quality number 9 pinion gears for the FWD transaxle. At the upper bound of gear feature tolerance, the processing time of primary machines which directly create features in the gear production line are halved, while at the tolerance limit the processing time is either increased by 50% or doubled, depending on the form of the curve, be it linear or 2^{nd} order.

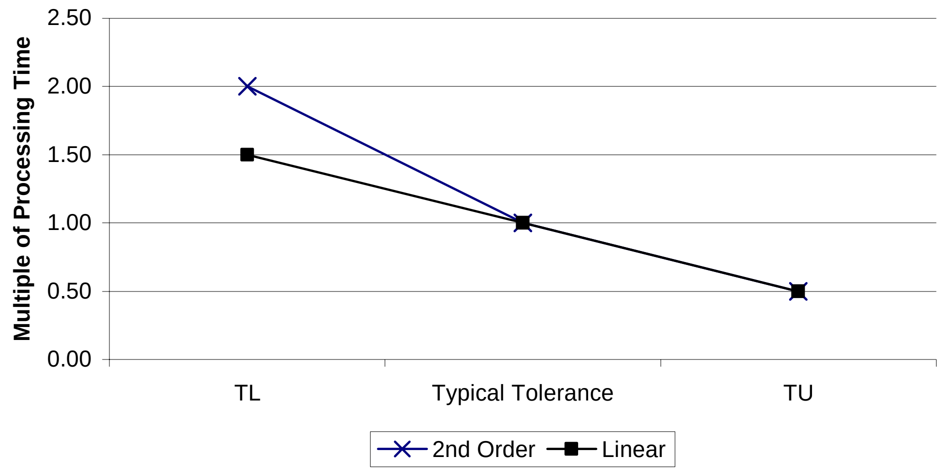


Figure 91 Multiple of Typical Processing Time as a Function of Gear Tolerance Level

In this study the hourly production rates (HPR) supported by auxiliary machines as a function of gear feature tolerance level will also be considered. As primary machine processing times decrease, their hourly production rates increase. Thus the hourly production rates of primary machines supported by auxiliary machines may be expected to increase with decreasing processing time which is associated with higher (i.e., looser) feature tolerance settings. Again, the known green finishing process will be used as the typical benchmark from which the performances of other tolerance levels for the same process plan may be generated. The multiplier of auxiliary HPR supported as a function of gear tolerance level is given in Figure 92.

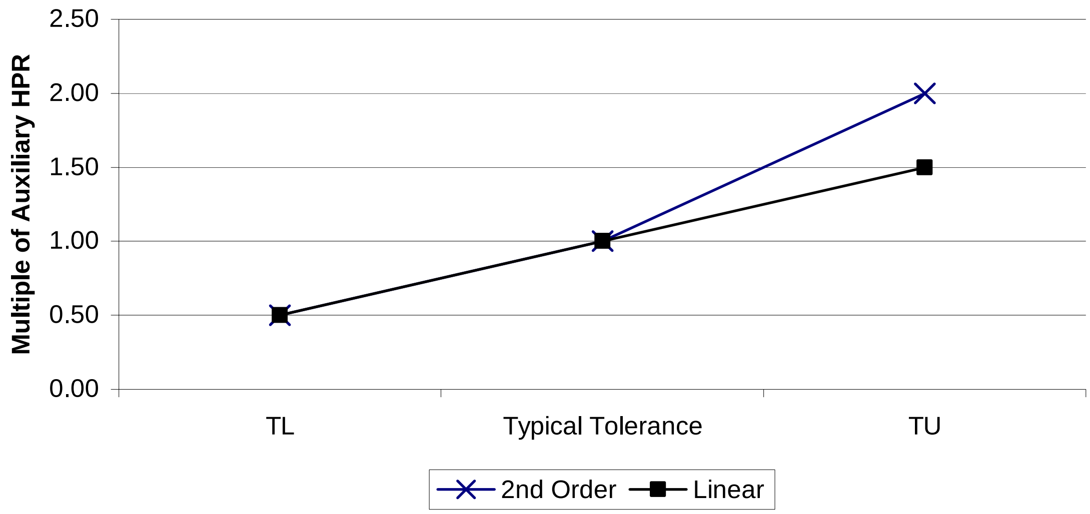


Figure 92 Multiple of Auxiliary HPR Supported as a Function of Gear Tolerance Level

The shape of the curve in Figure 92 is a mirror image of the curve in Figure 91. Unlike processing time, auxiliary HPR is directly related to tolerance level and increases with feature tolerances. The relationships in Figures 91 and 92 between the feature tolerance levels the green finishing process is capable of achieving and processing time and auxiliary HPR will be used in estimating the manufacturing performances of the green finishing process as a function of gear feature tolerances. Assuming that the process of green finishing presented in Section 7.6 is the benchmark for producing pinion gears at AGMA Quality number 9, the performance of that production line at its limits of tolerance capability are to be examined. Thus the production line's cost and environmental performances as a function of gear feature tolerance is determined, using the assumed relationships between feature tolerance level and processing time and auxiliary HPR.

Curves for these relationships were found using the following method. For each tolerance limit setting (i.e., the tolerance lower and upper bound) the processing times of the primary machines of the green gear finishing process which directly create gear features are altered by the factor specified in Figure 91 for that tolerance level. Varying the processing times jointly and not tweaking individual primary machines individual based on particular gear feature tolerances, will yield the widest performance estimate intervals. That is, at the tolerance limit setting all primary machines are adjusted for operation at that most precise tolerance requirements, and all gear features will be produced as precisely as possible. At the tolerance upper bound setting, all primary machines are adjusted for operation at the roughest tolerance requirement; all the features of the gear will be at a much looser tolerance level. The processing times of primary machines which directly create gear features are varied with respect to feature tolerance level requirements; the following primary machines in the green finishing process, though vital to the production of quality gears, do not directly create features and their processing times were not adjusted for the different tolerance levels: pre-heat treat washer, heat treat furnace, and the final washer. The operation of the washers may be safely assumed to be constant across all gear feature tolerance levels, but the operation of the heat treat furnace most likely has some response to the required gear feature tolerances. The heat treatment of transmission gears and the relationship with required feature tolerances is a complex subject that is not addressed here; the assumption is made that the heat treat furnace used in the pinion gear production process operates constantly across all feature tolerance requirements, but it is recognized that this assumption may be incorrect. The auxiliary HPR supported was also varied as a function of the gear feature tolerance level, per the relationship given in Figure 92. The addition of primary and auxiliary machinery required to maintain constant production volumes is not included in this study, but would induce jump discontinuities such as those seen in the parametric studies of Chapter 3.

Using the deterministic outputs from the Excel-based tool, the indicators of manufacturing performance of SPS, financial cost, and energy use are estimated at each gear feature tolerance level. Plots of these indicators as a function of gear feature tolerance are given in Figures 93, 94, and 95, respectively. The performance responses using the linear and 2nd order processing time – feature tolerance relations, as well as the inclusion of the varying of auxiliary HPR as a function of feature tolerance levels are all plotted in the Figures.

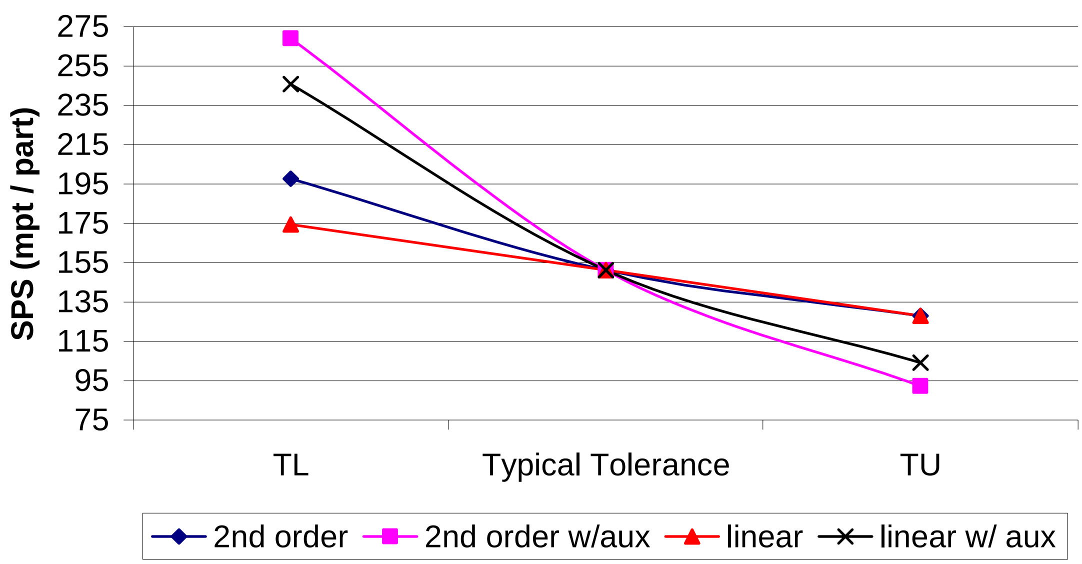


Figure 93 Green Finishing SPS as a Function of Gear Feature Tolerances

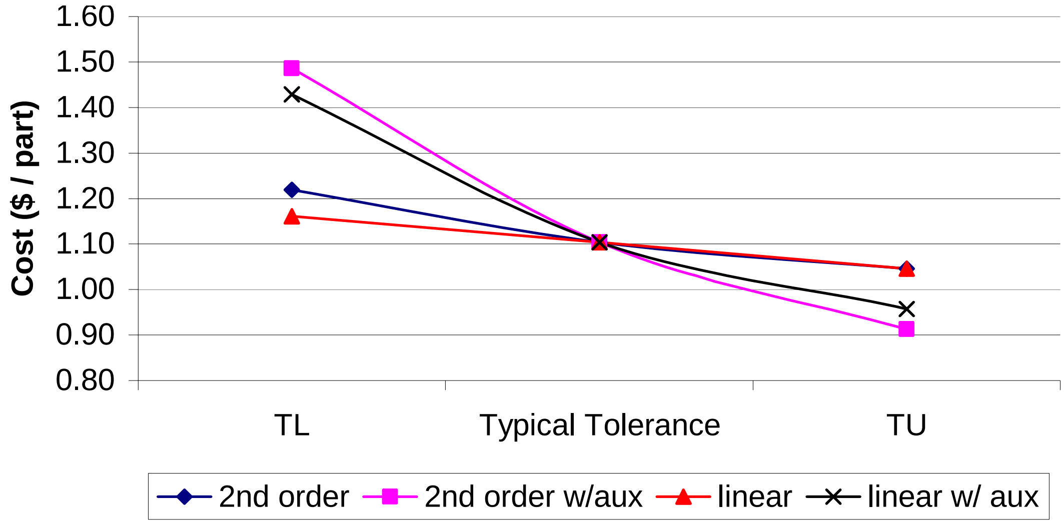


Figure 94 Green Finishing Financial Cost as a Function of Gear Feature Tolerances

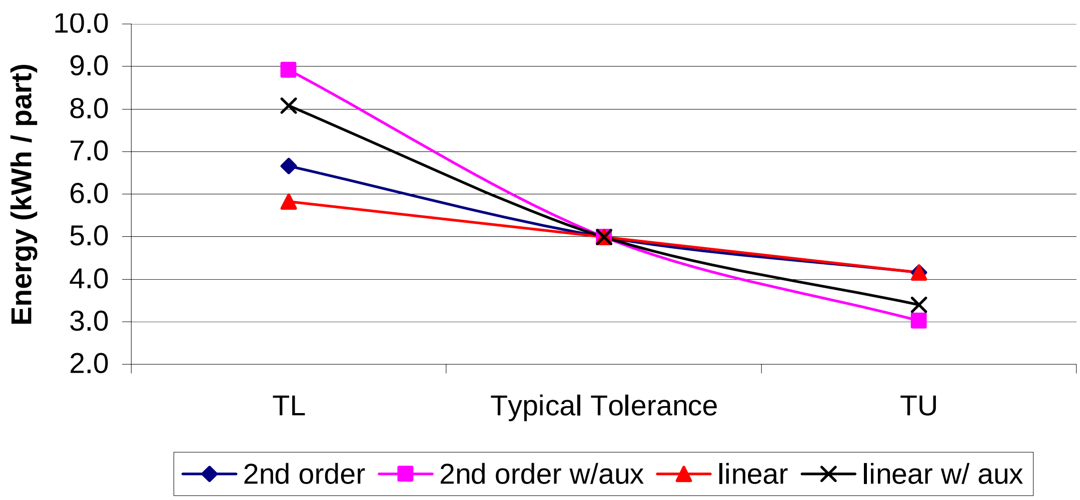


Figure 95 Green Finishing Energy Use as a Function of Gear Feature Tolerances

The performance responses are plotted with and without the varying of the auxiliary HPR supported as a function of feature tolerance because it is uncertain whether this will actually occur. For a constant production volume, regardless of gear feature tolerance requirements, the hourly production rate will be relatively constant as well. If feature tolerances are tightened to the extent that primary machine production rates drop below an allowable level, additional primary machines will most likely be added to keep the primary production at the required rate. Though an auxiliary machine may now support two primary machines instead of one, the output of those machines remains the rate required to meet production volume or schedule demands. Not considering a required production rate however, auxiliary HPR supported will vary as a function of feature tolerance level. Including the auxiliary HPR response to feature tolerance levels has a significant effect on the performance estimates shown above in Figure 93, 94, and 95. When a varying HPR is included it is seen that the estimates increase at the tolerance limit (i.e., performance is degraded), and at the upper bound the estimates decrease further (i.e., performance improves). In Table 51, the differences at the tolerance limit and the tolerance upper bound when variable auxiliary HPR is and is not included, for the manufacturing performance estimates are given. In Table 51, the linear model relating processing time to gear feature tolerance was used, but similar percentage differences are seen when the 2nd order model is used as well.

Table 51 Effect of Including Variable Auxiliary HPR on Performance Estimates

	Tolerance Limit			Tolerance Upper Bound		
Performance Indicator	**w/o aux**	**w/aux**	**% Difference**	**w/o aux**	**w/aux**	**% Difference**
SPS (mpt / part)	174	246	29.0%	128	104	22.9%
Cost ($ / part)	1.16	1.43	18.7%	1.05	0.96	9.3%
Energy (kWh / part)	5.8	8.1	28.0%	4.2	3.4	22.2%

The differences in performance estimates when auxiliary HPR is varied versus when it is held constant are rather significant. Therefore, when using the tool and conducting performance estimates it is critical to consider the response in auxiliary HPR to changing feature tolerance levels in addition to the response of the primary machine processing times.

Looking at the performance estimates as a function of tolerance level in Figures 93, 94, and 95 above, there is clearly some error in performance estimate accuracy when the assumption is made that process operation is constant or flat for all feature tolerance requirements. However, one wonders whether this error is acceptable and if performance estimates generated using typical process operation are good enough for decision making purposes. The errors in performance estimates at the bounds of the process' tolerance capability range (i.e., the tolerance limit and the tolerance upper bound) are given in Tables 52 and 53 below. The error is determined using the performance estimate found under the assumption typical process operation, and the performance estimates found at the bounds of the process feature tolerance capability range. In Table 52, the errors are given under the additional assumption of constant auxiliary HPR supported, while in Table 53 the variability of auxiliary HPR as a function of feature tolerance level is included and percentage errors are seen to increase further.

Table 52 Performance Estimate Errors Under Assumption of Typical Operation Across Tolerance Levels and Constant Auxiliary HPR

	Performance Indicator	TL	% Error	TU	% Error
Linear	SPS (mpt / part)	174	13.3%	128	18.2%
	Cost ($ / part)	1.16	5.0%	1.05	5.5%
	Energy (kWh / part)	5.8	14.3%	4.2	20.1%
2ndOrde	SPS (mpt / part)	198	23.5%	128	18.2%
	Cost ($ / part)	1.22	9.4%	1.05	5.5%
	Energy (kWh / part)	6.7	25.1%	4.2	20.1%

Table 53 Performance Estimate Errors Under Assumption of Typical Operation Across Tolerance Levels, Considering Variable Auxiliary HPR

	Performance Indicator	TL	% Error	TU	% Error
Linear	SPS (mpt / part)	246	38.5%	104	45.2%
	Cost ($ / part)	1.43	22.7%	0.96	15.3%
	Energy (kWh / part)	8.1	38.3%	3.4	46.8%
2ndOrde	SPS (mpt / part)	269	43.8%	92	63.9%
	Cost ($ / part)	1.49	25.7%	0.91	20.9%
	Energy (kWh / part)	8.9	44.1%	3.0	65.1%

The percentage errors seen in Table 52 and 53 are significant. The percentage error for the performance estimates at the tolerance limit indicate by how much an estimate calculated using typical process operation is *under* the performance estimate found using the more accurate correlations of feature tolerances and processing times. Similarly, the percentage error for the performance estimates at the tolerance upper bound indicate by how much an estimate calculated using typical process operation is *above* the more accurate performance estimate found using the feature tolerance and processing time relationship. If the errors are sufficiently small the penalty for making the assumption and simplification of process operation as constant as a function of feature tolerance may be acceptable. However, as the error increases beyond acceptable levels, a better understanding of the processing times as a function of gear feature tolerances is necessary for more accurately generating manufacturing performance estimates. In the earlier stages of product design, when process plans are not defined or even begun, a user of the tool most likely will not be to know or understand the specifics of process operation as a function of varying feature tolerance levels, and the typical operation characteristics will be assumed. Initial insight and feedback information on manufacturing performances will be valuable however, but the limitation and likely inaccuracy of the rough estimates must not be ignored.

The performance estimate errors for SPS and energy use are troublingly high, especially when the variability of auxiliary HPR as a function of feature tolerance is included. Given the known contribution of processing time as a main driver in the calculation of environmental burdens these estimates at the bounds of the process' feature tolerance capability range are clearly expected to differ from those calculated using typical processing time. The performance estimates of financial cost are off by a smaller amount than the errors of the SPS and energy use estimates. While much smaller, this difference is not negligible, and when the variability of auxiliary HPR is included the error of the estimated cost performance increases considerably. To minimize the inaccuracy of manufacturing performance estimates generated using the tool developed in this thesis, sufficient understanding of the production process components' (i.e., primary and auxiliary machines') behavior as a function of changing the dimensional tolerances of the features to be created.

A similar study will be conducted for the hard finished pinion gears, and the results compared, keeping in mind of course the lack of knowledge of the gear processes' actual tolerance capability ranges.

7.7. Hard Finished Pinion Gears

The pinion gears which are hard finished, and the RWD transmission into which they are assembled, have previously been introduced. The pinion gears are in a Ravigneaux configuration, and one simple planetary set, in the transmission. A listing of all the gears in the 6 speed RWD transmission, along with their quantities in the transmission, is giving in Table 54. There are fewer gears in this transmission compared to the FWD Transaxle; this fact is attributable to the fact that the final drive gears are not housed in the transmission itself, but are a separate entity in the vehicle's powertrain. Also, a common ring gear is utilized for the pinion-sun configurations.

Table 54 Gears in 6 Speed RWD Transmission

Name	Qty per Trans
Rear Short Pinion	3
Rear Long Pinion	3
Front Short Pinion	3
Front Sun	1
Rear Long Sun	1
Rear Short Sun	1
Ring Gear	1

Other than the pinion gears, there is only one of each gear per transmission and their annual production volume is the same as that of the transmission itself, here assumed to be 450,000 transmission per year. The annual quantities required of the pinion gears are multiples of the transmission quantity; they are listed in Table 55. Unlike the FWD Transaxle, the number of each of the pinion gears in the transmission is identical. Just as in the previous section, the annual quantities of the gears, and the pinion gears specifically here, along with the working hours per year, are used to determine the hourly production rate for a production line. Line dynamics such as uptime, defect fall out rates, and utilization are again not explicitly considered; hourly production rate is the number of finished, produced gears required in a working hour to meet the required annual volume, assuming equal distribution of the production over an entire working year.

Table 55 Hard Finished Pinion Annual Quantities

Name	Qty per Trans	Annual Qty
Rear Short Pinion	3	1350000
Rear Long Pinion	3	1350000
Front Short Pinion	3	1350000

The hard finish process used to manufacture the pinion gears is presented pictorially in Figure 96; just as in the green finishing process to produce pinion gears each of the three hard finished pinions has their own production line. The full list of machines used in the green finishing process, including the auxiliary machinery not pictured in Figure 96, is given in Figure 97.

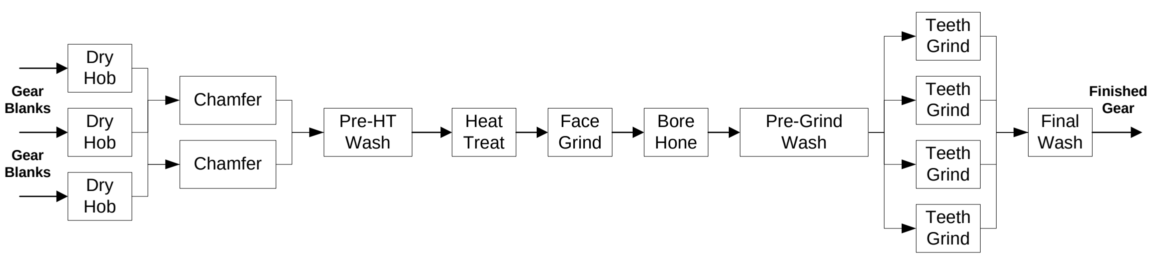


Figure 96 Hard Finish Process

Primary Machines	Auxiliary Machines
Dry Hob	Dust Collector
Chamfer	Mist Collector
Pre-HT Washer	Coolant System
HT Furnace	Chiller
Face Grinder	Material Handler
Bore Hone	External Loader
Pre-Grind Washer	
Teeth Grinder	
Final Washer	

Figure 97 Hard Finish Process

With the machines in the process spelled out, the tool developed to instantiate the proposed method may be employed. The listing of gear processing machines in Figure 97 are selected in the front end process generation portion of the developed tool; this selection is accomplished simply by choosing each machine in the hard finishing process from a listing of the available gear processing machines. These selected machines have their associated operating characteristic data extracted from the databases and are exported to the back end process accounting portion of the developed tool. The operating characteristic data imported into the back end feeds the mathematical models previously explained to generate estimates on the amounts of environmental burdens generated by the proposed process. Machine costs and labor costs are also calculated, and the environmental burdens used to determine the environmental impacts and single point environmental impact score, as well as the costs associated with utilities purchase and by-products disposition. To improve the accuracy of these estimates the steps discussed previously should be employed; specifically, the number of machines and hourly production rates supported by auxiliary machines should be updated to reflect the actual manufacturing process. In the case of early product design, this information is not likely known well, but since this analysis is of existing gear production lines, the numbers of machines and hourly production rates may be determined using the methods introduced in Chapter 3.

7.7.1. Number of Machines and Hourly Production Rates

When there is no sharing of machines between production lines determining the number of each machine and the hourly production rates of the auxiliary machinery is simple. However, the production of these pinion gears for the RWD transmission does not take place in isolation; not only are primary and auxiliary machines shared among the pinion gear lines, they are shared among the production lines for all of the gearing in the transmission. Therefore to properly attribute machine performance to the pinion gear of interest, the fractions of primary and auxiliary machine use for that pinion gear must be determined. The shared primary and auxiliary machinery present on the hard finishing gearing processes, and their quantity, are given in Table 55. These machines are not simply shared among the three pinion gear production lines; they are also used to support the production of all the gearing of the transmission.

Table 56 Shared Machinery for RWD Transmission Gearing Processes

Shared Primary Machinery		Shared Auxiliary Machinery	
Pre-HT Washer	1	Dust Collector	1
HT Furnace	4	Mist Collector	1
Final Washer	1	Coolant System	1

To determine the machine fractions for primary and auxiliary machines requires the use of Equations 7 for primary machine fractions, and Equations 15, 16, and 17 for auxiliary machine fractions, developed in Chapter 3. These equations are to be used because the differing production rates of the different gears causes unequal sharing of the machinery. Using the knowledge of the total numbers of gear primary machinery, production rates for each gear, and the primary operations which are supported by particular auxiliary machinery, the machine fractions may be computed. The number of machines and the support of primary machines by auxiliary for the RWD transmission are presented in Appendix C, including the machine fractions for all the gear production lines. The production rates for each gear may be determined using the assumed volume of transmissions in a year and the number of gears per transmission. Using this information and the Equations mentioned, the machine fractions may be calculated; for the hard finished pinion gears the number and fractions of machines is given in Table 57.

Table 57 Hard Finishing Process Machines

	Pinion:	Rear Short	Rear Long	Front Short
Primary	Dry Hob	3	4	2
	Chamfer		2	
	Pre-HT Washer		0.231	
	HT Furnace		0.923	
	Face Grinder		1	
	Bore Hone		1	
	Pre-Grind Washer		1	
	Teeth Grinder	4	5	4
	Final Washer		0.231	
Auxiliary	Dust Collector	0.3	0.4	0.2
	Mist Collector	0.269	0.313	0.269
	Coolant System	0.269	0.313	0.269
	Material Handler		11	
	External Loader		2	

To determine hourly production rates of the auxiliary support machinery Equations 18, 19, and 20 from Chapter 3 may be used. These equations are to be used because the differing production rates of the different gears causes unequal sharing of the machinery. Using the same information as required to calculate machine fractions for sharing (i.e., number and types of machines supported and productions rates), the auxiliary production rates may be found; these auxiliary production rates are presented in Tables 58. In Table 58 the hourly production rates of all the gear lines are also given for reference.

Table 58 Hourly Production Rates

Hourly Production Rates	
Dust Collector	960
Mist Collector	2720
Coolant System	2720
Material Handler	240
External Loader	240
Pinion Lines	240
Other Gear Lines	80

With the types and numbers of machines, and the auxiliary hourly production rates, specified, the developed tool is employed to generate estimates for the cost and environmental performances of this manufacturing process for the hard finished transmission pinion gears.

7.7.2. Manufacturing Performance Estimates for Hard Finished Pinions

The same procedure discussed in the previous section is followed to generate manufacturing performance estimates for the hard finished pinion processes. The manufacturing performance estimates for the three hard finished pinion gears of the RWD Transmission are presented in Tables 59, 60, and 61. The per-gear results of the uncertainty analysis are presented, with the mean (μ), standard deviation (σ), minimum, and maximum, along with the units for each indicator.

Table 59 Rear Short Pinion Process Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	309	26.8	240	406	mpt / part
Financial Cost	2.04	0.214	1.55	2.66	$ / part
Water Use	4.0	0.39	3.4	5.8	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.29	0.053	0.19	0.38	lb / part
Special Waste	0.37	0.010	0.35	0.39	lb / part
Energy	10.0	0.86	7.7	13.1	kWh / part
CO2	13.30	1.147	10.30	17.45	lb / part

Table 60 Rear Long Pinion Process Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	334	27.3	261	418	mpt / part
Financial Cost	2.23	0.227	1.70	2.91	$ / part
Water Use	4.0	0.39	3.4	5.6	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.38	0.071	0.26	0.50	lb / part
Special Waste	0.46	0.013	0.44	0.48	lb / part
Energy	10.8	0.88	8.4	13.5	kWh / part
CO2	14.44	1.177	11.27	18.04	lb / part

Table 61 Front Short Pinion Process Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	299	26.2	240	391	mpt / part
Financial Cost	1.98	0.202	1.54	2.53	$ / part
Water Use	4.0	0.37	3.4	5.6	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.19	0.035	0.13	0.25	lb / part
Special Waste	0.37	0.010	0.35	0.39	lb / part
Energy	9.6	0.83	7.7	12.5	kWh / part
CO2	12.80	1.113	10.27	16.71	lb / part

The Monte Carlo simulations iterated hundreds of times in each analysis. Given the uncertainty of machine information in the databases, knowledge of the resulting uncertainty in performance estimates is critical. As a caveat, the lack of information for some items in the machine databases must be factored in to decision making; an estimate of zero for an indicator does not necessarily mean that there is zero of that item. The three hard fished pinion gears all have similar designs, and thus the similarity in manufacturing performances is expected. Using the deterministic results from the tool, a comparison of the three gears' performances in their manufacture is given in Table 62.

Table 62 Comparison of Hard Finished Pinion Process Environmental and Cost Performance Estimates

		Rear Short Pinion	Rear Long Pinion	Front Short Pinion	units
Main	Environmental SPS	308	333	298	mpt / part
	Financial Cost	2.04	2.23	1.97	$ / part
Inventory	Water Use	3.9	4.0	3.9	gal / part
	Landfill Waste	0.00	0.00	0.00	lb / part
	Recyclable Material	0.29	0.38	0.19	lb / part
	Special Waste	0.37	0.46	0.37	lb / part
	Energy	9.9	10.8	9.6	kWh / part
	CO2	13.28	14.41	12.76	lb / part

The interesting thing to note in Table 62 is the general similarity of each of the pinion gears' manufacturing performances. The number of each type of pinion gear per transmission is constant, but the number of key primary processing machines is not. There are different numbers of the dry hob and post heat treatment teeth grinding machines; this fact is the driver for the differences in costs, the amounts of recyclable material and special wastes generated, energy used, and CO_2 emitted. Given that the gear blanks and designs are fairly similar, there should not be such a difference in the amounts of by-products generated in manufacture. This situation highlights a weakness of the method; typical machine performance data is used to estimate these indicators, and when the actual operation differs from what is typical, misleading estimates may follow. Since the gear designs are so similar, the amounts of recyclable material and special wastes generated should be about the same, irrespective of the number of the primary processing machines in place in the production which generate these by-products, since the material to be removed from the parts is roughly the same. For example, the rear long pinion has five teeth grinders, compared to only four for both the rear short and front short pinions. The five teeth grinders on the rear long pinion line should have the same part throughput as the four teeth grinders on each of the other pinion lines, since there are equivalent numbers of parts per transmission, and also same by-products generated, though less per machine. Differing processing times may be expected which will then drive higher attribution of environmental burdens (and thus costs and environmental impacts) to units of production, but the number of machines will not change the amount of by-products generation related directly to material removal.

The estimates of zero for landfill waste for all of the hard finished pinion gears are suspect. The amount per gear is miniscule, and does not show up with three decimal places, and the landfill waste generation rates are not adequately known for the machinery in these processes. This warrants further investigation to ascertain the actual operating behavior / characteristics of these machines; particularly the dust and mist collectors since they are clearly known to collect by-products from machine operations.

Averaging the manufacturing performance of the three hard finished pinion gears, yields a somewhat representative picture of hard finished pinion gear manufacture, with an AGMA Quality number of 11. The averages of the deterministic tool estimates, as well the estimates from the uncertainty analyses, are given in Table 63. Per statistical arithmetic, to find the standard deviation of the average mean required averaging the standard deviations of the three pinion gears, and then dividing by the square root of 3.

Table 63 Average Hard Finished Pinion Process Environmental and Cost Performance Estimates

			MC Output		
		Tool Output	μ	σ	**units**
Main	Environmental SPS	313	314	15.5	mpt / part
	Financial Cost	2.08	2.09	0.124	$ / part
Inventory	Water Use	3.9	4.0	0.22	gal / part
	Landfill Waste	0.00	0.00	0.000	lb / part
	Recyclable Material	0.29	0.29	0.031	lb / part
	Special Waste	0.40	0.40	0.006	lb / part
	Energy	10.1	10.1	0.50	kWh / part
	CO2	13.48	13.52	0.661	lb / part

In addition to the requirements for tighter tolerances placed on transmission gearing to achieve component and system level design objectives, another factor influences the decision to hard finish: the requirement that the manufacturing facility be capable of meeting gear geometries. Hard finishing is the safest way to remove the somewhat unpredictable heat treatment induced geometry distortion in gears, which may cause a reduction in process capability (Cpk), perhaps below allowed levels. Addressing quality issues of out-of-spec gears reactively is likely both expensive and inefficient to the manufacturer: rework, scrapped parts, undesirable effects at higher level assemblies (chiefly, NVH), and worst case, recalls. A hard finishing process for pinion and other transmission gears, though initially more expensive than green finishing, can provide good value by allowing for better control of the final gear geometries, which may help the manufacturer to avoid potentially devastating quality costs and reactionary corrective measures. While cost has been the main decision driver between hard and green finishing of pinion gears, the environmental aspects and implications of such a decision are and should be given increasing weight in these decision making processes. The method proposed in this thesis is an attempt to further and support this effort. A comparison of the green and hard finished pinion gears follows a parametric study of the manufacturing performance of the hard finished pinions.

7.7.2.1. A Parametric Study of Hard Finishing Performances

The operation and performance of the hard finished gear processes to produce the specific pinions for the 6-speed RWD transmission has been discussed. These hard finished pinion gears may be generally characterized by an AGMA Quality number classification of 11; this Quality number is a measure of the tolerance specifications of various features of the designed pinion gears. The hard finishing processes have been designed and implemented for the production of these particular pinion gears, but it is expected that for the hard finishing process some range in gear feature tolerances may be achieved, depending on the particular operation of the machines in the process.

Similar to the parametric studies conducted in Chapter 3 to understand the behavior of the environmental burden models as a function of feature tolerances, the manufacturing performance behavior of the hard finishing process selected and implemented to produce AGMA Quality classification 11 pinion gears, as a function of the gear feature tolerances, will be examined here. The specific tolerance limits of the hard finishing process for pinion gears are not known. An assumption is made that the characterization of the specific hard finishing process for these pinions gears is of the typical operation; thus the production of AGMA Quality number 11 pinion gears may be considered the mid-point within the process' gear feature tolerance capability spectrum. In reality however, simply assigning an AGMA Quality number does not have the necessary fidelity to adequately specify all the gear feature tolerances required, and the location of these pinion gears in the hard finishing process's gear feature tolerance capability spectrum is unknown. For the sake of discussion here however the pinions will be assumed to be located squarely in the middle of this tolerance capability range, as the 'typical' tolerance achieved by the process. Using the known hard finishing process whose operation information is housed in machine databases, manufacturing performance estimates for other gears produced via this process with different feature tolerance requirements, though still within the process capability, may be generated. The same processing time and auxiliary HPR as function s of gear feature tolerance level given in Section 7.6.2.1 will be used, along with the same method for conducting the study.

Using the deterministic outputs from the Excel-based tool, the indicators of manufacturing performance of SPS, financial cost, and energy use are estimated at each gear feature tolerance level. Plots of these indicators as a function of gear feature tolerance are given in Figures 98, 99, and 100, respectively. The performance responses using the linear and 2nd order processing time – feature tolerance relations, as well as the inclusion of the varying of auxiliary HPR as a function of feature tolerance levels are all plotted in the Figures.

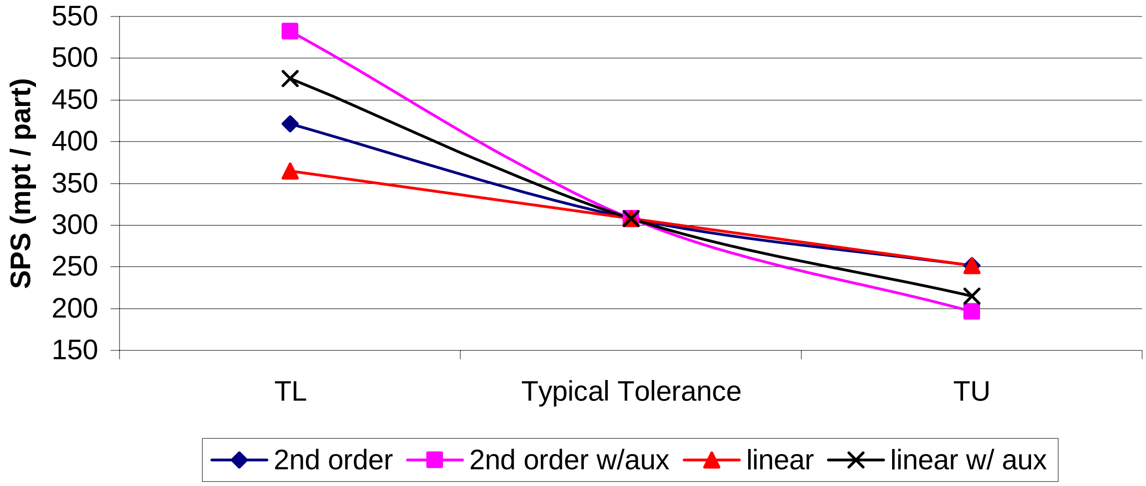


Figure 98 Hard Finishing SPS as a Function of Gear Feature Tolerances

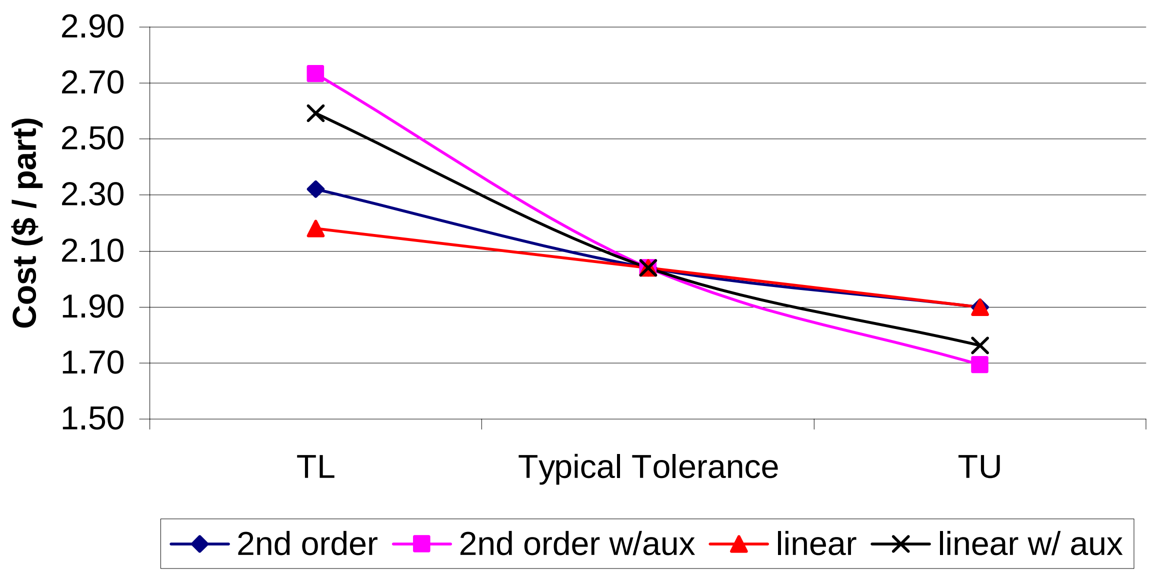


Figure 99 Hard Finishing Financial Cost as a Function of Gear Feature Tolerances

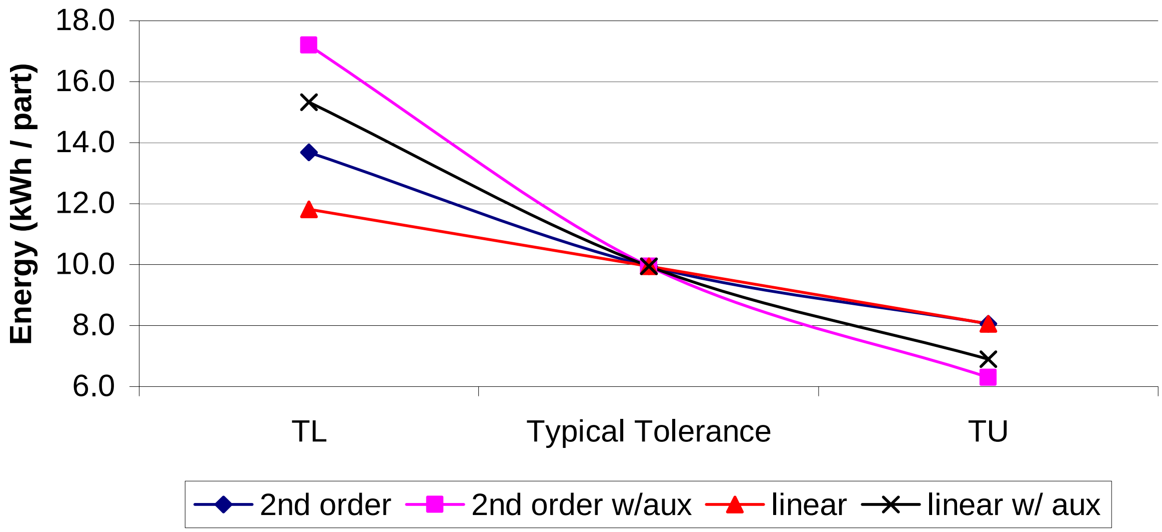


Figure 100 Hard Finishing Energy Use as a Function of Gear Feature Tolerances

The performance responses are plotted with and without the varying of the auxiliary HPR supported as a function of feature tolerance because it is uncertain whether this will actually occur. Including the auxiliary HPR response to feature tolerance levels has a significant effect on the performance estimates shown above in Figure 98, 99, and 100. When a varying auxiliary HPR is included it is seen that the estimates increase at the tolerance limit (i.e., performance is degraded), and at the upper bound the estimates decrease (i.e., performance improves). In Table 64, the differences at the tolerance limit and the tolerance upper bound when variable auxiliary HPR is and is not included, for the manufacturing performance estimates are given. In Table 64, the linear model relating processing time to gear feature tolerance was used, but similar percentage differences are seen when the 2nd order model is used as well.

Table 64 Effect of Including Variable Auxiliary HPR on Performance Estimates

	Tolerance Limit			Tolerance Upper Bound		
Performance Indicator	**w/o aux**	**w/aux**	**% Difference**	**w/o aux**	**w/aux**	**% Difference**
SPS (mpt / part)	365	476	23.3%	252	215	17.2%
Cost ($ / part)	2.18	2.59	15.8%	1.90	1.76	7.8%
Energy (kWh / part)	11.8	15.3	23.0%	8.1	6.9	17.0%

The differences in performance estimates when auxiliary HPR is varied versus when it is held constant are rather significant. Therefore, when using the tool and conducting performance estimates it is critical to consider the response in auxiliary HPR to changing feature tolerance levels in addition to the response of the primary machine processing times.

Looking at the performance estimates as a function of tolerance level in Figures 98, 99, and 100 above, there is clearly some error in performance estimate accuracy when the assumption is made that process operation is constant or flat for all feature tolerance requirements. The errors in performance estimates at the bounds of the process' tolerance capability range (i.e., the tolerance limit and the tolerance upper bound) are given in Tables 65 and 66 below. The error is determined using the performance estimate found under the assumption typical process operation, and the performance estimates found at the bounds of the process feature tolerance capability range. In Table 65, the errors are given under the additional assumption of constant auxiliary HPR supported, while in Table 66 the variability of auxiliary HPR as a function of feature tolerance level is included and percentage errors are seen to increase further.

Table 65 Performance Estimate Errors Under Assumption of Typical Operation Across Tolerance Levels and Constant Auxiliary HPR

	Performance Indicator	TL	% Error	TU	% Error
Linear	SPS (mpt / part)	365	15.5%	252	22.4%
	Cost ($ / part)	2.18	6.5%	1.90	7.4%
	Energy (kWh / part)	11.8	15.9%	8.1	23.2%
2ndOrde	SPS (mpt / part)	421	26.8%	252	22.4%
	Cost ($ / part)	2.32	12.1%	1.90	7.4%
	Energy (kWh / part)	13.7	27.4%	8.1	23.2%

Table 66 Performance Estimate Errors Under Assumption of Typical Operation Across Tolerance Levels, Considering Variable Auxiliary HPR

	Performance Indicator	TL	% Error	TU	% Error
Linear	SPS (mpt / part)	476	35.2%	215	43.5%
	Cost ($ / part)	2.59	21.3%	1.76	15.8%
	Energy (kWh / part)	15.3	35.2%	6.9	44.2%
2ndOrde	SPS (mpt / part)	532	42.1%	196	57.1%
	Cost ($ / part)	2.73	25.3%	1.69	20.4%
	Energy (kWh / part)	17.2	42.2%	6.3	57.6%

The percentage errors seen in Table 65 and 66 are significant. The percentage error for the performance estimates at the tolerance limit indicate by how much an estimate calculated using typical process operation is *under* the performance estimate found using the more accurate correlations of feature tolerances and processing times. Similarly, the percentage error for the performance estimates at the tolerance upper bound indicate by how much an estimate calculated using typical process operation is *above* the more accurate performance estimate found using the feature tolerance and processing time relationship. If the errors are sufficiently small the penalty for making the assumption and simplification of process operation as constant as a function of feature tolerance may be acceptable. However, as the error increases beyond acceptable levels, a better understanding of the processing times as a function of gear feature tolerances is necessary for more accurately generating manufacturing performance estimates.

The performance estimate errors for SPS and energy use are troublingly high, especially when the variability of auxiliary HPR as a function of feature tolerance is included. Given the known contribution of processing time as a main driver in the calculation of environmental burdens these estimates at the bounds of the process' feature tolerance capability range are clearly expected to differ from those calculated using typical processing time. The performance estimates of financial cost are off by a smaller amount than the errors of the SPS and energy use estimates. While much smaller, this difference is not negligible, and when the variability of auxiliary HPR is included the error of the estimated cost performance increases considerably. To minimize the inaccuracy of manufacturing performance estimates generated using the tool developed in this thesis, sufficient understanding of the production process components' (i.e., primary and auxiliary machines') behavior as a function of changing the dimensional tolerances of the features to be created.

7.8. Comparison of Green vs. Hard Finished Pinion Gears

The manufacturing cost and environmental performance estimates for green and hard finished transmission pinion gears have been generated using the method and tool proposed by this thesis. These performance estimates will be compared to ascertain a more complete and quantified picture on the differences. The comparison will first be conducted using the averages of the indicators representative of the different methods for finishing; the deterministic estimates directly from the tool will be used. The effect of uncertainty in the estimates will be considered in the comparison of two individual pinion gears, one green finished and the other hard finished. Before looking at representative green and hard finished pinions and making comparisons, there are two different bases for which to make comparisons of interest. The comparisons of deterministic manufacturing performance estimates on per transmission and per year bases are given in Tables 67 and 68, respectively. Both the RWD transmission and the FWD transmission were assumed to have yearly production volumes of 450,000, but there are differing numbers of pinion gears in each; there are 9 total pinions in the RWD transmission (4.05 million pinions per year), and 12 total pinions in the FWD transaxle (5.4 million pinions per year). These performance estimates in Tables 67 and 68 only consider the pinion gears, and do not include all other gearing in the transmission (i.e., sun gears, ring gears, and final drive gears in the FWD transaxle only).

Table 67 Per Transmission, Environmental and Cost Performance Estimates of Pinion Processes

		Hard Finish	Green Finish	units
Main	Environmental SPS	2818	1755	mpt / trans
	Financial Cost	18.75	10.69	$ / trans
Inventory	Water Use	35.5	39.0	gal / trans
	Landfill Waste	0.00	0.00	lb / trans
	Recyclable Material	2.58	3.41	lb / trans
	Special Waste	3.61	0.00	lb / trans
	Energy	90.8	58.0	kWh / trans
	CO2	121.34	77.49	lb / part

Table 68 Per Year, Env. and Cost Performance Estimates of Pinion Processes

		Hard Finish	Green Finish	units
Main	Environmental SPS	1,268,216	789,798	pt / yr
	Financial Cost	8,435,580.83	4,809,658.26	$ / yr
Inventory	Water Use	15,955.9	17,542.6	1000 gal / yr
	Landfill Waste	--	9.72	lb / yr
	Recyclable Material	580.2	766.1	ton / yr
	Special Waste	812.0	0.4	ton / yr
	Energy	40,870	26,100	MWh / yr
	CO2	27,301	17,435	ton / yr

Even with these functional unit bases, the hard finished pinion gears are predominantly lower performing in terms of manufacturing costs and environmental impacts. Since the FWD transaxle, with its green finished pinions, has more of the pinion gears some of the indicators are higher though; water use and recyclable material generated are higher. Per gear requirements for water use drive this indicator upwards with the additional pinion gears, and removing approximately the same amount of material from additional pinion gears in the FWD transaxle causes the recyclable material indicator to increase as well. Also of note is the huge relative difference in special wastes between the hard and green finished gears; this difference is also seen on a per gear basis discussed next, but on a larger scale this difference stands out significantly. This huge difference may be attributed to the post heat treat teeth grinding operations for the pinion gears of the RWD transmission, and the grinding sludge and swarf by-products that result from it. Sludge and swarf by-products, categorized as special wastes, result from operations common to both the hard and green finishing processes (e.g., honing the gear bore, grinding the thrust faces), but this amount is clearly not as significant as that generated by the teeth grinding in hard finishing.

Changing the basis back to per-gear, the representative hard finished and green finished pinion gears are compared below in Table 69. From these per gear estimates, the relative differences may be found by dividing the indicator for hard finished pinion by that of the green finished pinion; the relative difference is thus the multiple of how much more 'expensive' the hard finish process is per pinion gear compared to the green finished pinion gear. A relative difference less than one would indicate that the green finished pinion gear is worse performing in manufacturing than the hard finished gear for that indicator. The relative differences between the green and hard finished pinion gears are presented in Table 70. Despite the fact that the machine information housed in the machine databases has been intentionally altered by a factor, the relative differences are still valid because the factor is cancelled out in calculating the relative difference. The values reported in Table 69 however, are representative, but off by this factor.

Table 69 Per Part, Env. and Cost Performance Estimates of Pinion Processes

		Hard Finish	Green Finish	units
Main	Environmental SPS	313	147	mpt / part
	Financial Cost	2.08	0.92	$ / part
Inventory	Water Use	3.9	3.1	gal / part
	Landfill Waste	0.00	0.00	lb / part
	Recyclable Material	0.29	0.28	lb / part
	Special Waste	0.40	0.00	lb / part
	Energy	10.1	4.9	kWh / part
	CO2	13.48	6.48	lb / part

Table 70 Relative Differences Between Green and Hard Finished Pinion Gears

		Relative Differences
Main	Environmental SPS	2.13
	Financial Cost	2.27
Inventory	Water Use	1.26
	Landfill Waste	--
	Recyclable Material	1.01
	Special Waste	2500.12
	Energy	2.08
	CO2	2.08

The relative differences shown in Table 70 are all greater than 1, indicating that hard finished pinion gears are across the board worse performing in manufacturing than green finished pinion gears. Recyclable material is right about 1, which indicates no difference in the amount of recyclable material generated by either process, which is to be expected given the similarity in the gear macro designs. Water use is only slightly higher, while all the other environmental performance indicators show at least a two-fold decrease in performance for hard finished pinions over green finished ones. Special waste, which has been previously discussed for the per transmission and per year bases, is hugely different between the two finishing processes. The post heat treat teeth grinding operations of the hard finishing process is the culprit in this difference.

Recalling the discussion on the cost of gear processing earlier in this chapter, the relative difference in cost between the green and hard finished pinion gears was predicted to be around 2.00 to 2.17 using the graph in Figure 87. The cost estimates generated by this proposed method find a relative difference of 2.27, which confirms this prediction! These predicted relative cost differences are given in Table 71.

Table 71 Predicted Relative Cost Differences

	Relative Cost Difference
AGMA	2.00
DIN	2.17
Predictor Tool	2.27

Though not fully validating this of this new method, it is reassuring and perhaps builds some degree of confidence into the method. Confidence is instilled because predicted cost values are not entirely off-base; given that the method's cost estimate predictions are in the same order of magnitude, and in fact match very closely, those predictions (albeit rough) generated using the standards of AGMA and DIN and established gear manufacturing cost trends, there is hope that the predicted environmental performance indicators will be likewise reasonable and valid. Validation of the environmental performance aspects of the method by a similar mean as by using Figure 87 is not possible yet because a gear quality (i.e., feature tolerance level) – environmental performance relationship is not yet established.

It appears that environmental impact score somewhat follows the financial cost difference. The relative difference for environmental SPS is 2.13, compared to 2.27 for financial costs. Whether this similarity in difference is a generalizable rule or fact, or simply the result specific to this individual case study, is not currently known. More studies are needed to test the hypothesis that environmental performance in manufacturing follows costs in manufacturing, and is not addressed here. This would be an interesting finding given the desire to make environmental initiatives more desirable to manufacturers from a business standpoint.

The same caveat for landfill waste needs mentioning; the estimates of zero for landfill waste for the pinion gears is suspect. The amounts per gear is miniscule, and does not show up with three decimal places, and the landfill waste generation rates are not adequately known for the machinery in these processes. This warrants further investigation to ascertain the actual operating behavior / characteristics of these machines; particularly the dust and mist collectors since they are clearly known to collect by-products from machine operations.

Plotting the values in Table 69 on a graph with axes like those in Figures 3 and 87, with performance on the y-axis as a function of tolerance on the x-axis, the following plots are given. The gear feature tolerances achieved by hard finishing are tighter than those achieved by the green finishing process. Finishing process (hard or green) is used as a proxy to the actual gear feature tolerance since there are numerous gear features and the exact role of each on process planning and manufacturing is unknown. Environmental impact score and financial costs are plotted versus finishing process in Figure 101; recyclable material, special wastes, and water use are plotted versus finishing process in Figure 102; and energy use and CO_2 generation are plotted versus finishing process in Figure 103. Landfill wastes are not plotted because it is estimated with the current machine information that zero (or practically zero and negligible) landfill waste is generated per part by either process, a suspicious claim. Appropriate units are found on either the left or right hand side y-axes, and straight lines are sketched between data points.

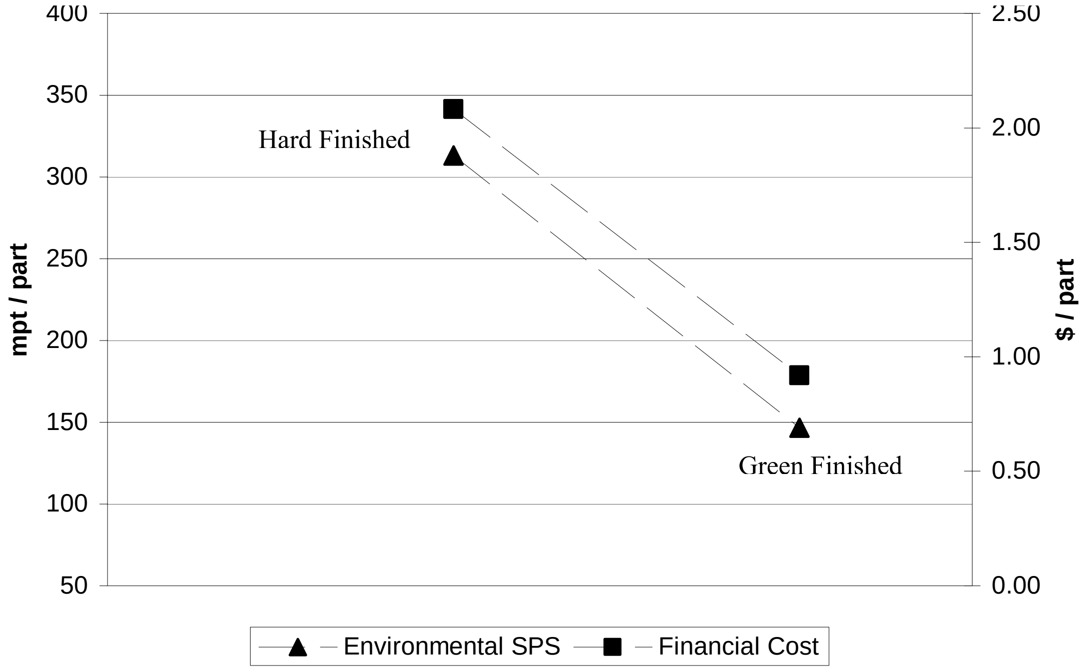


Figure 101 Plot of Env. Impact Score and Financial Cost vs. Finishing Process

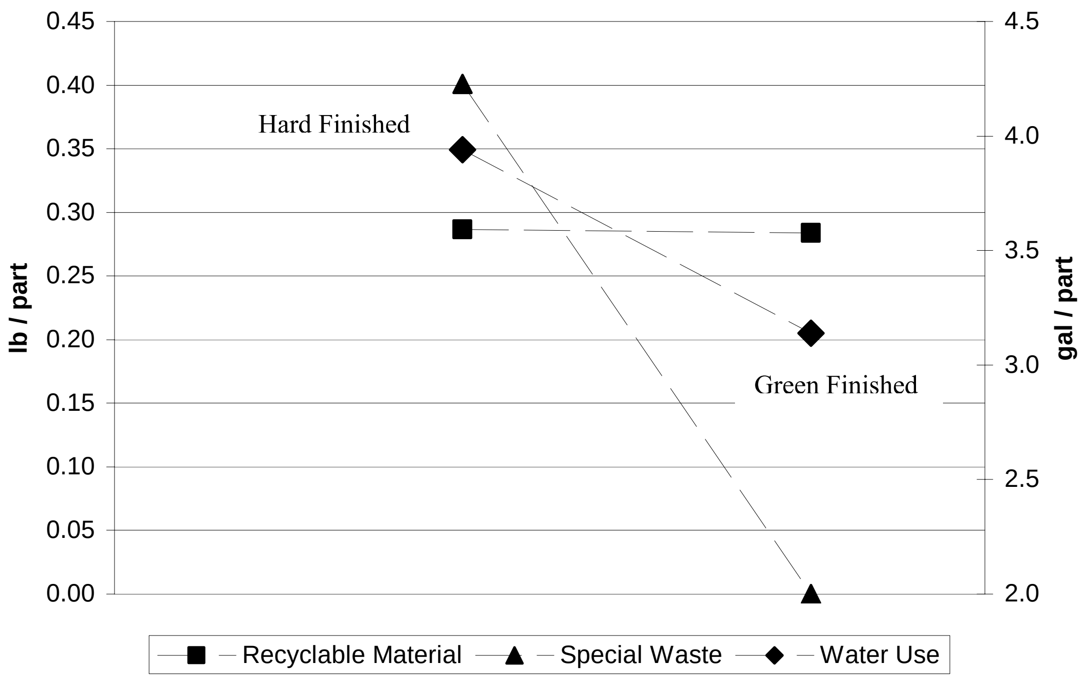


Figure 102 Plot of Recyclable Material, Special Wastes, and Water Use vs. Finishing Process

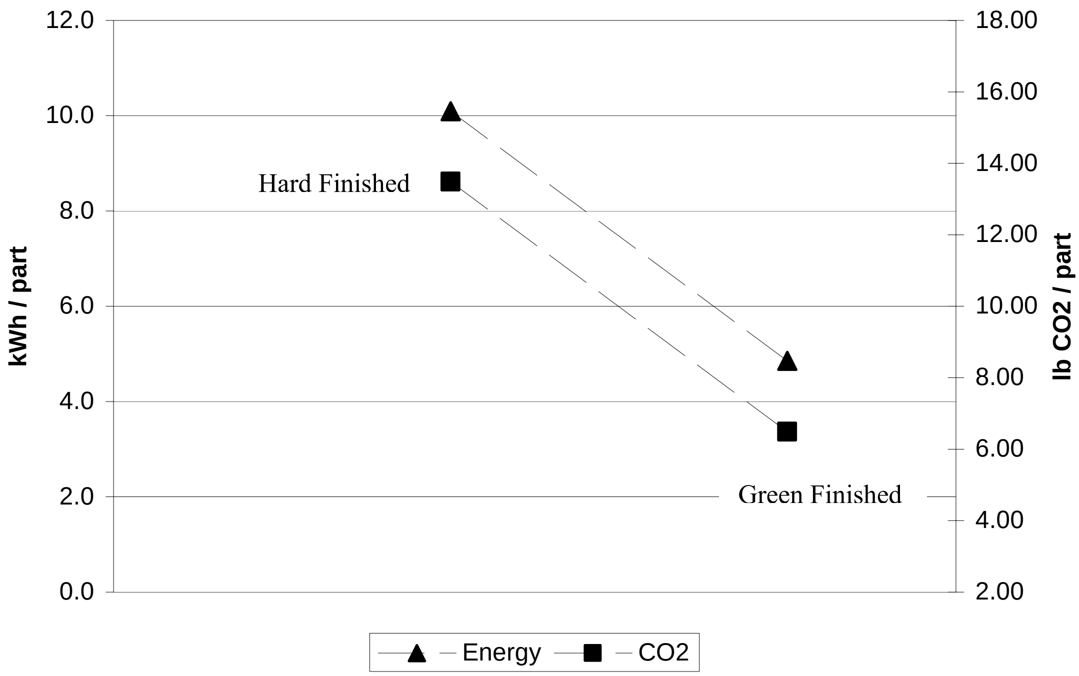


Figure 103 Plot of Energy Use and CO_2 Generation vs. Finishing Process

Recyclable material is seen as practically constant in Figure 102, regardless of the finishing process. Based on the assumption that the recyclable materials of the process result primarily from the dry cutting operations used to cut teeth (i.e., hobbing), and given that the pinion gears are similar in size, the amount of material removed per part, feeding the amount of recyclable material generated, should be constant.

With the findings of this case study, it is not yet possible to generate an environmental performance as a function of gear feature tolerance relationship because there are only two point estimates. One can draw a line between the two points, and assume a linear relationship, but the actual relationship is unknown. There is risk involved in attempting to draw conclusions from only two data points; other data points are necessary to prove a general trend. Though it's not expected given the known shape of Figures 3 and 87, the relationship between tolerance and other performance indicators, namely environmental, could be highly non-linear with peaks or discontinuities. Additional investigation of real manufacturing operations, with complete machinery databases is needed to better understand and develop a relationship between part feature tolerances and environmental performance in manufacturing. However, the findings of the case study are useful in giving a rigorous, quantified estimate of 'by how much' more expensive, both in terms of financial costs and environmental impacts, the decision to hard finish transmission pinion gears is over green finishing them. Phrased another way, estimates of potential environmental and cost savings associated with green finishing, and not hard finishing, pinion gears are found. The manufacturing performance estimates for the two gear finishing processes may be used to more rigorously support future gear design decisions, when manufacturing performance is weighed against other important product life cycle considerations.

7.8.1. Comparison of Parametric Studies

In this section the results of the parametric studies of manufacturing performance estimates for both the green and hard finished pinion gear processes will be compared. Essentially for each finishing method, required due to differing gear feature tolerance requirements, the performance of the chosen process, with its unique processing steps and selected primary and auxiliary machinery, resulting from its operation, which is influenced strongly by the required gear feature tolerances, is given as a function of gear feature tolerance level. In these comparisons the linear processing time –feature tolerance relationship is used; also, the addition of primary or auxiliary machinery required to meet production volumes is not considered. The manufacturing performance plots as a function of process tolerance levels for the green and hard finishing processes are plotted in the same Figure. The comparison of SPS, financial cost, and energy use of the pinion gear's manufacture are given in Figures 104, 105, and 106, respectively. The x-axes in Figures 104, 105, and 106 are the tolerance level of gear features, but are intentionally not valued because the specific feature tolerance capabilities of the two gear processes are not known explicitly. The items on the x-axes are the hard finishing process tolerance limit (HF TL), the hard finishing process upper bound on tolerance (HF TU), the green finishing process tolerance limit (GF TL), and the green finishing process upper bound on tolerance (GF TU). Additionally, the location of the pinion gears of the case study in the process tolerance capability spectrum is indicated by the AGMA Quality classification number, assumed to be at the mid-point of their respective production process. As a reminder, the green finished reaction pinion may be classified as having an AGMA Quality number of 9, and the hard finished rear short pinion may be classified as having an AGMA Quality number of 11.

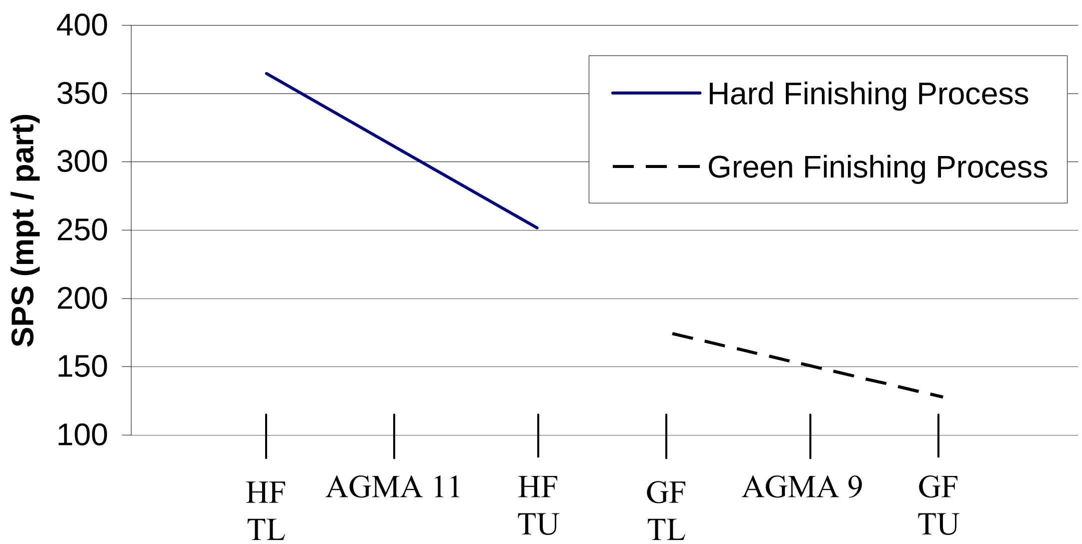


Figure 104 SPS of Pinion Gears as a Function of Tolerance Level

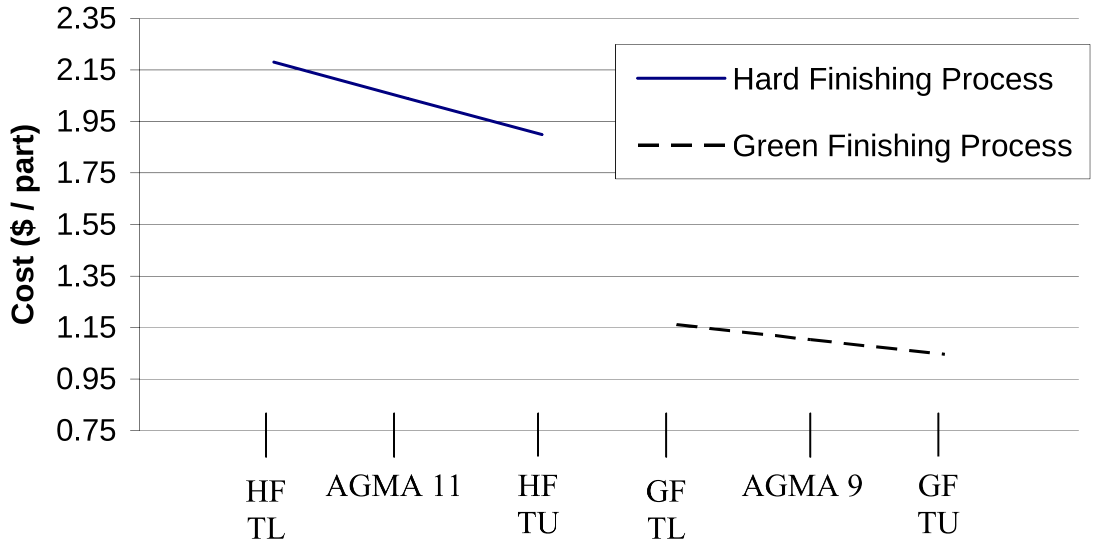


Figure 105 Financial Cost of Pinion Gears as a Function of Tolerance Level

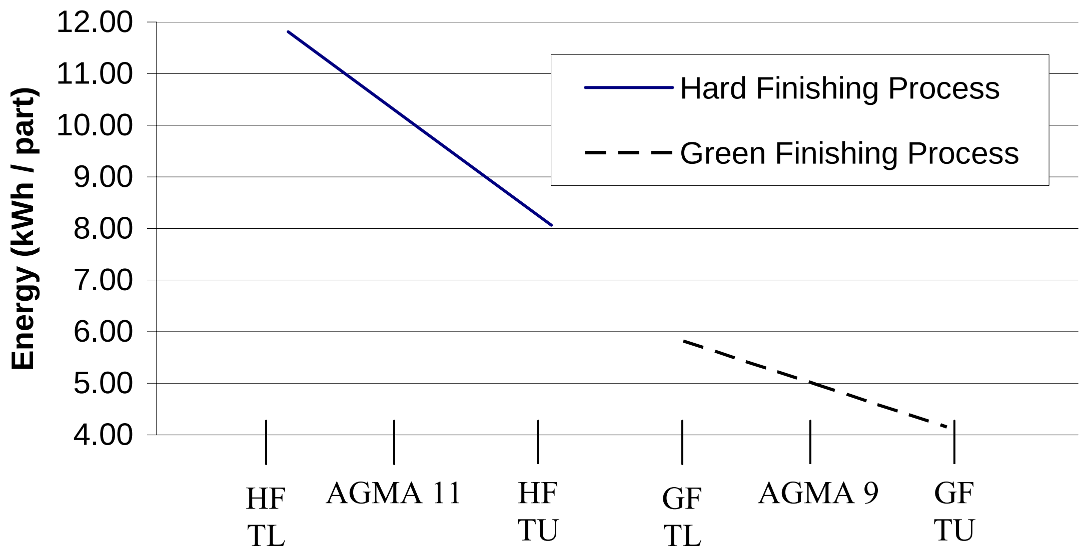


Figure 106 Energy of Pinion Gears as a Function of Tolerance Level

The exact locations of the upper and lower bounds on process feature tolerance capability are unknown. If the upper bound of tolerance capability of the hard finishing process is greater than or equal to the tolerance limit of the green finishing process, there is some overlap in the processes to achieve certain gear feature tolerance levels. For performance curves which intersect within this range, the intersection gives those gear feature tolerance values at which the manufacturing performances of the green finishing and hard finishing processes are equivalent! However, this situation is expected to be a fairly rare occurrence given the innate differences between green and hard finishing production processes, namely the increased complexity of hard finishing. A hypothetical situation which is more likely to happen is depicted in Figure 107; the upper bound of tolerance capability of the hard finishing process is greater than the tolerance limit of the green finishing process, creating an overlap of tolerance capability. The indicator of manufacturing performance shown in Figure 107 is SPS, but is representative of all the indicators of manufacturing performance.

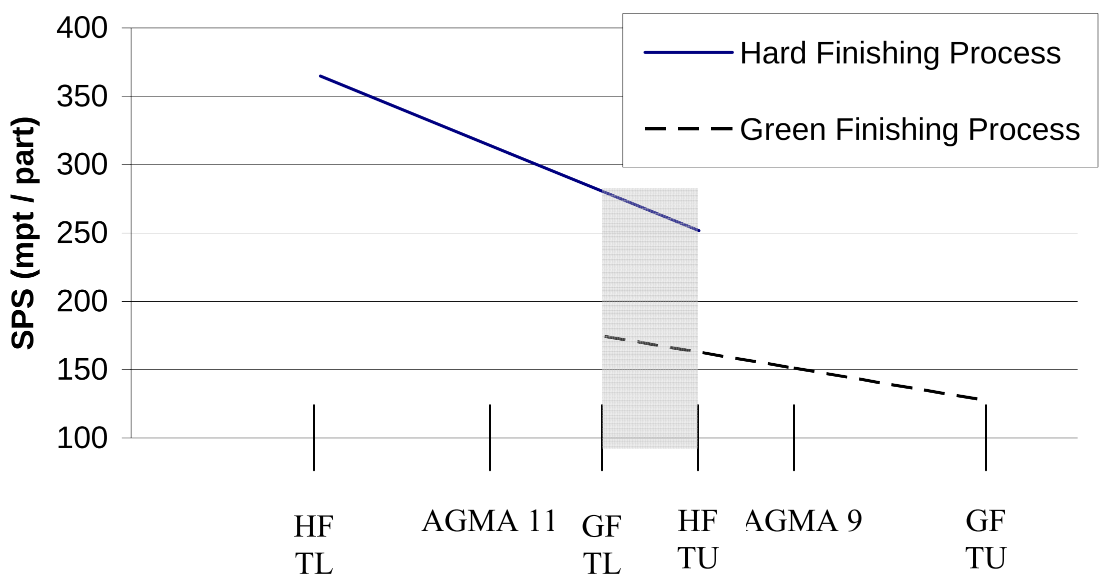


Figure 107 Overlap Situation of Process Tolerance Capabilities

To produce gears in the tolerance overlap region of Figure 107, it is seen that the environmental performance of the gear manufacture, as measured by SPS, will *always* be better for the green finishing process because the curves in Figure 107 will never intersect in the shaded tolerance overlap region.

The plots in Figures 104, 105, and 106 are more insightful when contrasted with the comparison plots in Figures 101, 102, and 103. The range of manufacturing performance as a function of gear feature tolerance is given, versus the single point estimates of manufacturing performance of the hard and green finished pinion gears. Those single point estimates of Figures 101, 102, and 103 are still depicted in Figures 104, 105, and 106, but are now contained in the performance curves as a function of gear feature tolerance. Those specific points are found at the mid-point of the respective curves.

The comparisons conducted up to this point have been done using the deterministic performance estimates generated by the Excel-based tool. The next comparisons will incorporate the uncertainty associated with machinery operating characteristics and thus the uncertainty in performance estimates found using Monte Carlo simulation.

7.8.2. Comparison of Interval Analyses

Before jumping into the comparison of probabilistic manufacturing performance estimates found using Monte Carlo simulation, an interval analysis will be conducted to determine the absolute bounds within which performance estimates may be expected. There are uncertain inputs to the mathematical models for estimating manufacturing performances contained in the machine databases and also the cost database. These uncertain inputs were modeled as uniform distributions with lower and upper bounds, and within that range any value is equally probable. Conducting an interval analysis yields the absolute maximum and minimum performance estimates possible by selecting the extreme upper or lower bound of the uniform distribution, as necessary, and computing a best case – worst case estimate. In this study, the worst case performance estimates (i.e., with the highest values) were computed using the upper bound of the uniform distributions on machine environmental burden rates, processing times, and cost rates; also, where they were uncertain, machine batch sizes were set at the lower bound of their uniform distribution. The best case performance estimates, with the lowest values, were computed by using the other bound of the uniform distribution for their respective input. After setting these extreme values for inputs to the performance estimate calculations, the indicators of manufacturing performance were generated and recorded. Additionally, the machine fractions and auxiliary hourly production rates supported of the green finished reaction pinion and the hard finished rear short pinion were used. Using this method to conduct an interval analysis on both green and hard finished pinion gears, the best and worst resulting manufacturing performance estimates were generated; they are presented in Table 72.

Table 72 Interval Ranges for Manufacturing Performance Estimates for Green and Hard Finished Pinion Gears

	Green Finish		Hard Finish		
	Best	**Worst**	**Best**	**Worst**	**units**
Environmental SPS	124	187	240	406	mpt / part
Financial Cost	0.84	1.46	1.55	2.66	$ / part
Water Use	2.0	4.1	3.4	5.8	gal / part
Landfill Waste	0.00	0.00	0.00	0.00	lb / part
Recyclable Material	0.19	0.38	0.19	0.38	lb / part
Special Waste	0.00	0.00	0.35	0.39	lb / part
Energy	4.1	6.2	7.7	13.1	kWh / part
CO2	5.46	8.27	10.30	17.45	lb / part

The interval ranges for the green and hard finished pinion gear manufacturing performance estimates in fact agree with the minimum and maximum estimates, as expected, previously found for the green finished reaction pinion and hard finished rear short pinion using Monte Carlo simulation and shown in Tables x and y, respectively. To more easily compare the performance estimate intervals in Table 72, these items are plotted in Figures 108 – 112. The intervals of SPS, financial cost, water use, recyclable material, and energy use for each pinion gear are each compared. Landfill waste is not compared because the insufficient database entries yield estimates of zero for both gears, special wastes are not compared because for the green finish process the estimate is zero, and CO_2 is not compared because it is determined linearly from the energy use.

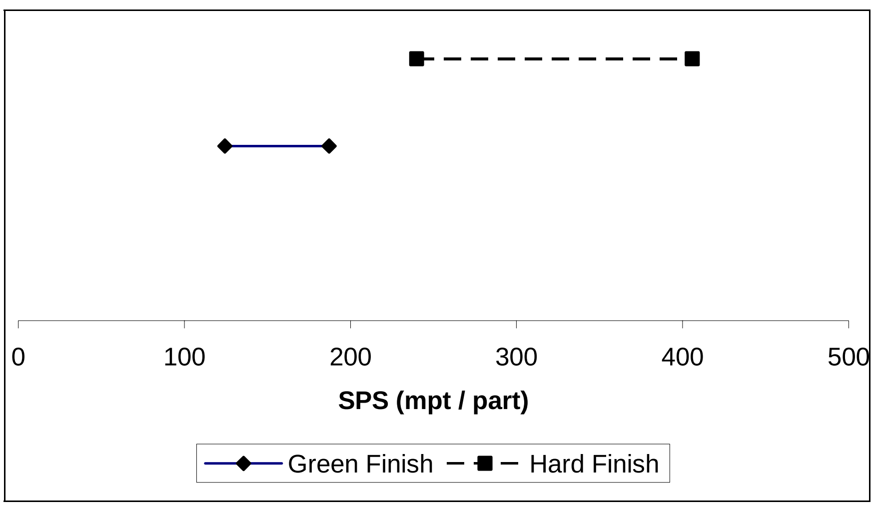


Figure 108 Interval Comparisons for SPS

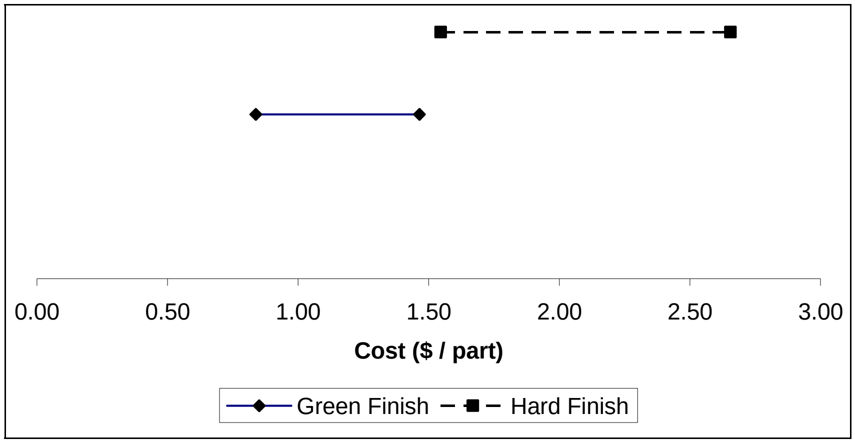


Figure 109 Interval Comparisons for Financial Cost

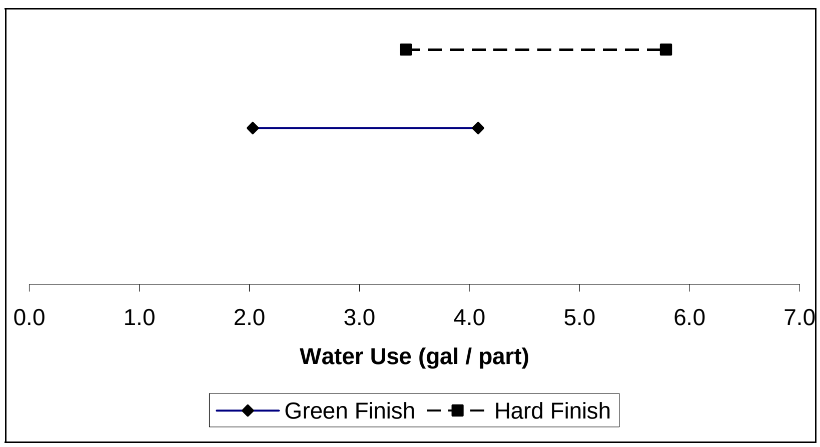


Figure 110 Interval Comparisons for Water Use

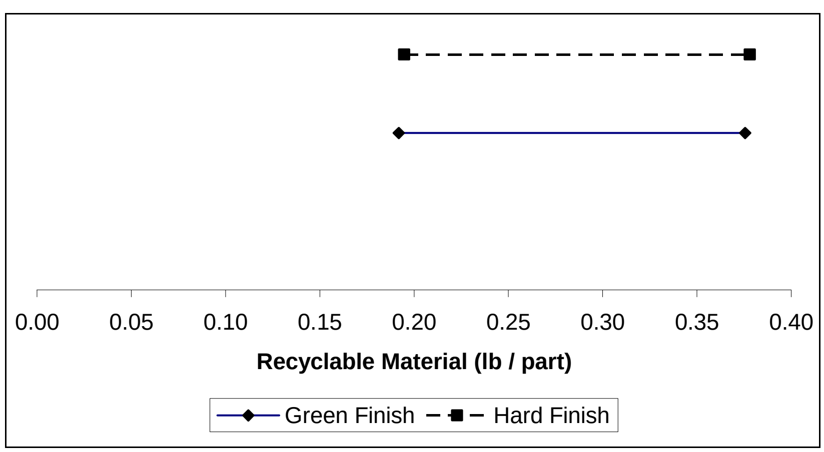


Figure 111 Interval Comparisons for Recyclable Material

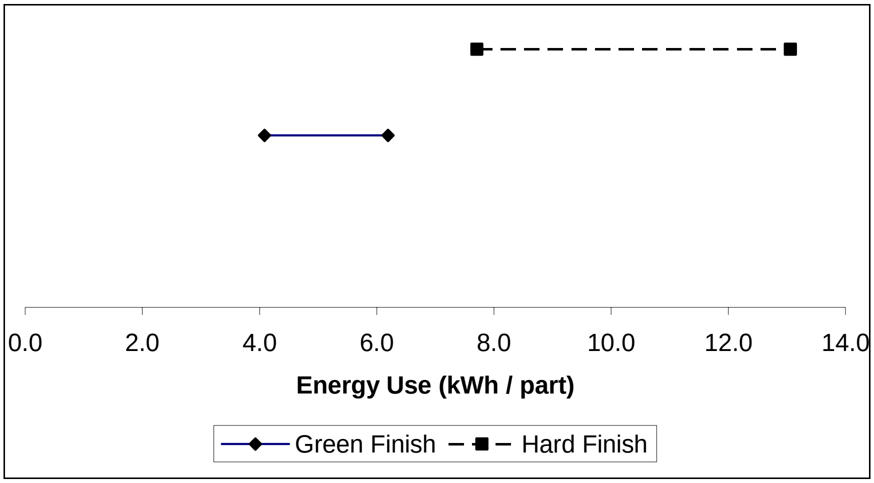


Figure 112 Interval Comparisons for Energy Use

The tighter intervals seen in Figures 108, 109, and 112 for SPS, financial cost, and energy use, respectively, of the green finished pinion result from narrower input uncertainties and may be used to explain the differing widths (i.e., standard deviations) of estimates in the next section as normal distributions. The specific uncertain inputs which contribute heavily to more uncertain performance estimates (i.e., those with wider spreads) will be fully explored in the next section.

There is overlap seen only in recyclable material and water use, which indicates that there is some probability that the differences in these particular manufacturing performance estimates for the two different gear manufacturing processes will become statistically insignificant in some cases. With the results of the interval analyses to understand uncertainty determining the exact probability at which these overlaps will occur may not be ascertained. Assuming that performance estimates are uniformly distributed within the estimate interval a probability may be determined looking at the width of the overlap relative to each estimate's interval width. However, the assumption of uniformly distributed performance estimates within an interval is most likely incorrect;

the extreme bounds of the performance estimate intervals are given, and it is not possible for estimates to occur outside of these bounds, but the actual probability distributions within the intervals are not known. To understand the shape of the distributions within the bounds of the intervals, Monte Carlo simulation is employed and the comparisons of probabilistic manufacturing performance estimates of the two pinion gears is given in the next section.

7.8.3. Uncertainty in Manufacturing Performance Estimate Comparisons

The uncertainty about and gaps in the machine databases have been discussed previously, and their impacts on manufacturing performance estimates clear. Thus, it is important that the uncertainty in these estimates be considered when making comparisons. Here two individual pinion gears are examined on the basis of estimates resulting from Monte Carlo simulation; the hard finished rear short pinion gear from the RWD transmission, and the green finished reaction pinion from the FWD transaxle. Before jumping into the estimates from the uncertainty analyses, their deterministic performance estimates are presented in Table 73 and are shown to agree with the trends presented for representative hard and green finished pinion gears: environmental SPS, financial cost, energy use, and CO_2 generation for the rear short pinion are all double that of the reaction pinion; recyclable material generated is similar for both; special waste substantially larger for the rear short pinion over the reaction pinion; and water use for the rear short pinion about 1.6 times that of the reaction pinion.

Table 73 Comparison of Deterministic Manufacturing Performance Estimates

	Pinion:	Rear Short	Reaction	units
Main	Environmental SPS	308	151	mpt / part
	Financial Cost	2.04	1.10	$ / part
Inventory	Water Use	3.9	2.5	gal / part
	Landfill Waste	0.00	0.00	lb / part
	Recyclable Material	0.29	0.28	lb / part
	Special Waste	0.37	0.00	lb / part
	Energy	9.9	5.0	kWh / part
	CO2	13.28	6.66	lb / part

These deterministic performance estimates however given no insight into the shape or spread of the actual performance. This may be achieved using Monte Carlo simulation; the probabilistic results for the same manufacturing performance estimates for the two pinion gears of interest are given in Table 74.

Table 74 Comparison of Probabilistic Manufacturing Performance Estimates

	Pinion:	Rear Short		Reaction		
		μ	σ	μ	σ	units
Main	Environmental SPS	309	26.8	153	11.3	mpt / part
	Financial Cost	2.04	0.214	1.11	0.117	$ / part
Inventory	Water Use	4.0	0.39	2.5	0.37	gal / part
	Landfill Waste	0.00	0.000	0.00	0.000	lb / part
	Recyclable Material	0.29	0.053	0.28	0.053	lb / part
	Special Waste	0.37	0.010	0.00	0.000	lb / part
	Energy	10.0	0.86	5.0	0.38	kWh / part
	CO2	13.30	1.147	6.72	0.502	lb / part

In addition to knowledge of the mean and standard deviation of the performance indicators, the minimum and maximum values are noted. Using these values and assuming normal distribution of the performance indicators, plots are generated of the shape of each estimated indicator to facilitate comparisons. The x-axis is the value of the estimate, and the y-axis is the probability of realizing that estimate value; integrating under the curve will yield a value of 1. Comparisons of the hard finished rear short pinion and the green finished reaction pinion are made in the following figures; environmental impact score in Figure 113, financial cost in Figure 114, water use in Figure 115, recyclable material in Figure 116, and energy use in Figure 117. Landfill waste is not plotted because its estimate is zero for both gears, special waste is not plotted because the estimate is zero with no uncertainty for the reaction pinion making a comparison trivial and uninteresting, and CO_2 is not plotted because it matches identically the shape of the energy plot.

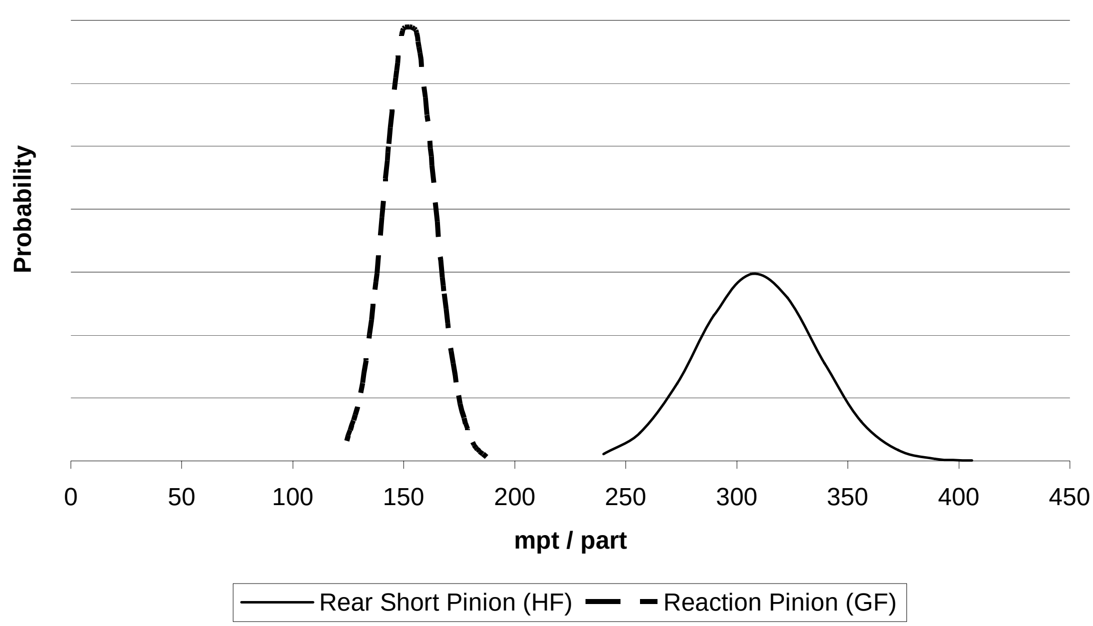


Figure 113 Environmental Impact Score Comparison

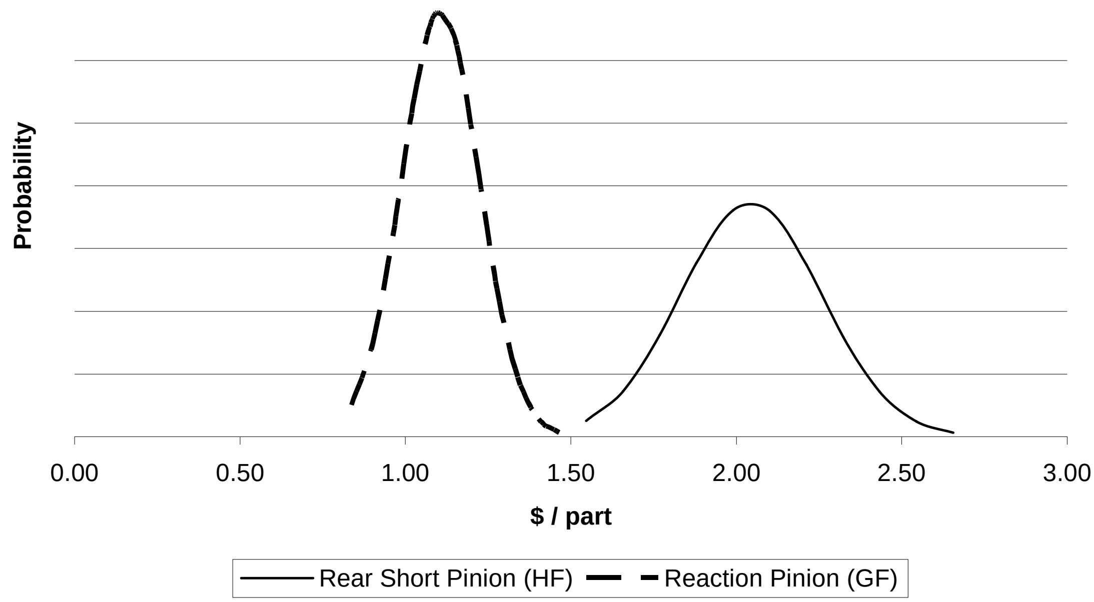


Figure 114 Financial Cost Comparison

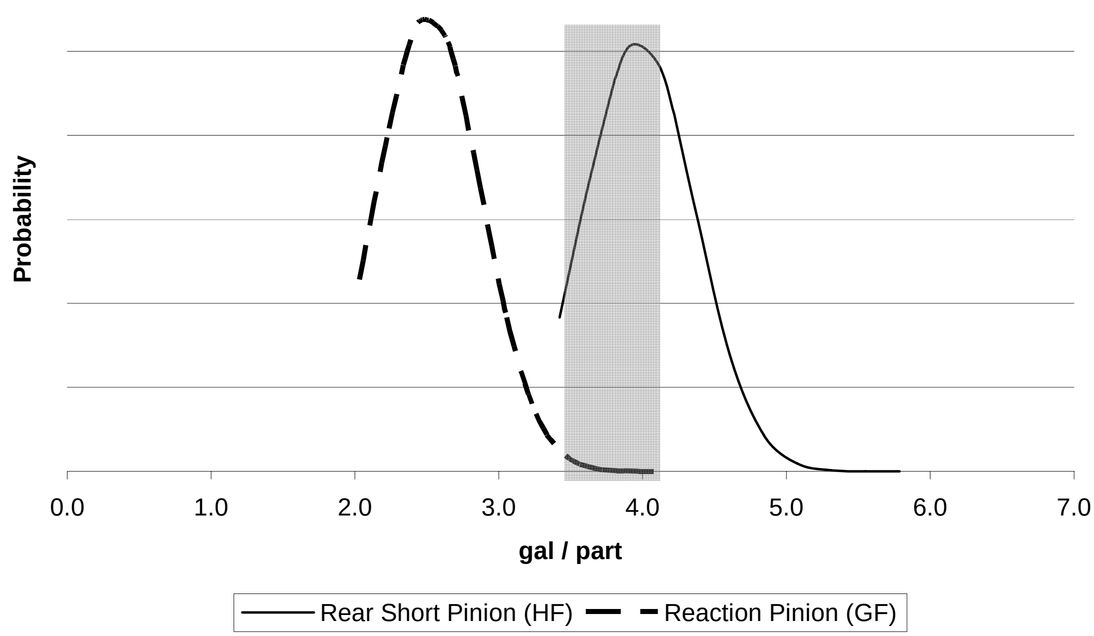


Figure 115 Water Use Comparison

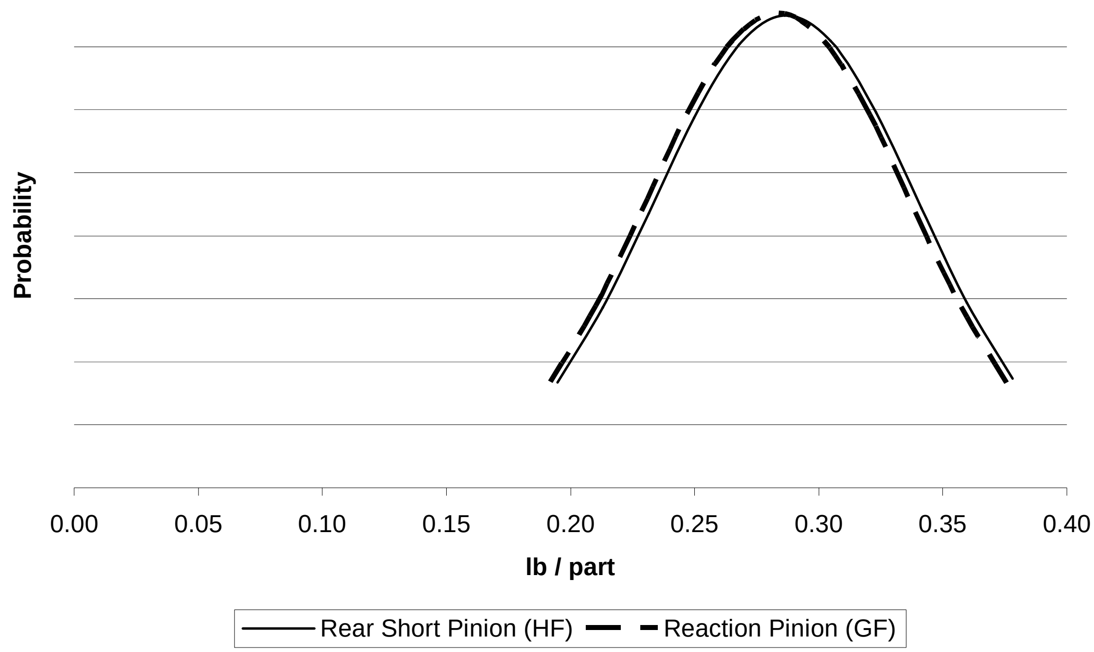


Figure 116 Recyclable Material Comparison

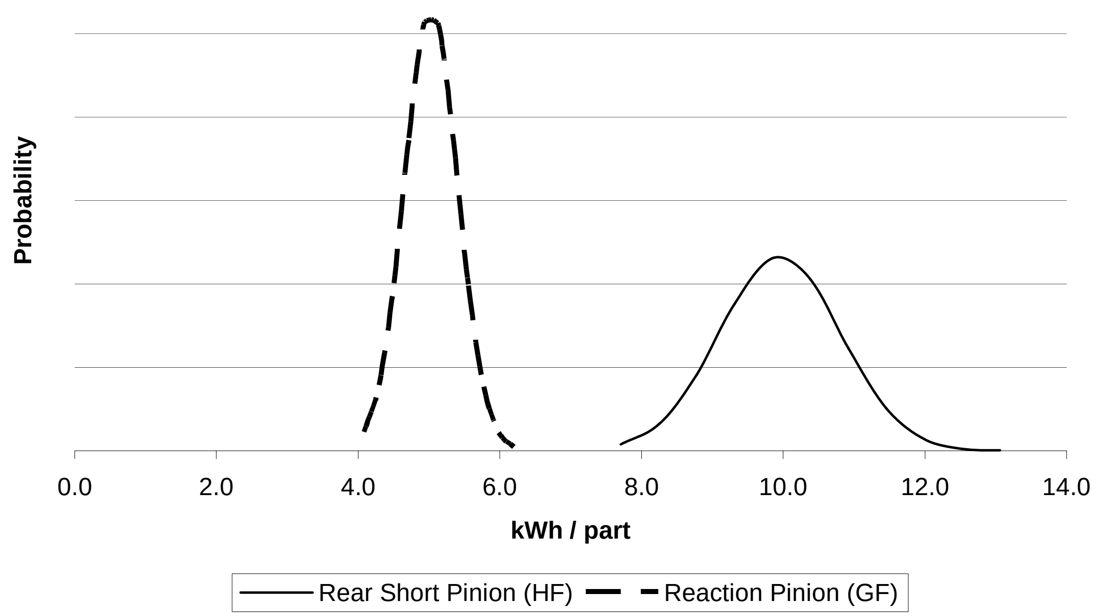


Figure 117 Energy Comparison

7.8.3.1. <u>Insight Into Different Performance Estimate Uncertainties</u>

The first item for discussion regarding the comparison plots in Figures 113 – 117 is the differing widths or spreads of the performance indicator estimates of SPS, financial cost, and energy for the hard finished rear short pinion, and the green finished reaction pinion. Looking at Table 74 the differences in plotted distribution shapes is to be expected given the different size standard deviations for the estimates of SPS, financial costs, and energy between the two pinion gears. The standard deviations of these indicator items are given below in Table 75.

Table 75 Standard Deviations of Manufacturing Performance Estimates for Green and Hard Finished Pinion Gears

Pinion:	Rear Short (HF)	Reaction (GF)	units
Environmental SPS	26.8	11.3	mpt / part
Financial Cost	0.214	0.117	$ / part
Energy	0.86	0.38	kWh / part

Looking in Table 75 it is seen that the standard deviations of the performance estimates calculated for the hard finished rear short pinion are about twice as large as the standard deviations of the performance estimates for the green finished reaction pinion. This is confirmed by quickly glancing at Figures 113, 114, and 117; the plotted distributions for the green finished pinion are considerably narrower than those of the hard finished pinion. The source of the difference between the standard deviations may be uncovered by examining the results from the sensitivity analyses performed with @RISK on these performance estimates. The sensitivity analyses will highlight the most significant uncertain inputs to the calculation of these indicator estimates. Discussed as a weakness previously, sensitivity analyses in @RISK only return those inputs which are modeled as uncertain using @RISK input functions, and not all model inputs. In this situation however this knowledge is useful in gaining insight into the differences in estimate uncertainties; since the estimate uncertainties for SPS, financial cost, and energy of the hard finished pinion are twice as large as the green finished pinion estimate uncertainties, it is expected that the most significant inputs to the hard finished pinion estimates will be more uncertain than those of the green finished pinion estimates. The ten most significant inputs, with their regression coefficients, to estimates of SPS, financial cost, and energy, for the reaction pinion and the rear short pinion are given in Tables 76, 77, and 78, respectively. As a side note, the higher the absolute value of a regression coefficient, the more significant the input. Also, summing the squares of the regression coefficients gives the R^2 value; an R^2 value of 1.00 indicates that every single input to the performance estimate has been accounted for, so a high R^2 value means that the most significant inputs to estimate calculation have been given.

Table 76 Sensitivity Analysis Results for SPS

Finish: Green
Pinion: Reaction

Rank	Name	Regr
#1	HT Furnace / Electrical Power (kW)	0.580
#2	Dry Hob / Processing Time (min)	0.498
#3	Bore Hone / Processing Time (min)	0.458
#4	Bore Hone / Batch Size	-0.308
#5	Bore Hone / Compressed Air (cfm)	0.186
#6	Bore Hone / Electrical Power (kW)	0.083
#7	Dry Hob / Electrical Power (kW)	0.053
#8	Final Washer / Batch Size	-0.052
#9	Material Handler / Electrical Power (kW)	0.042
#10	Face Grinder / Electrical Power (kW)	0.032
	R^2	0.940

Finish: Hard
Pinion: Rear Short

Rank	Name	Regr
#1	Pre-Grind Washer / Compressed Air (cfm)	0.486
#2	Pre-Grind Washer / Processing Time (min)	0.469
#3	HT Furnace / Electrical Power (kW)	0.413
#4	Teeth Grinder / Compressed Air (cfm)	0.287
#5	Teeth Grinder / Electrical Power (kW)	0.273
#6	Dry Hob / Processing Time (min)	0.205
#7	Bore Hone / Processing Time (min)	0.202
#8	Bore Hone / Batch Size	-0.134
#9	Chamfer / Compressed Air (cfm)	0.123
#10	Bore Hone / Compressed Air (cfm)	0.076
	R^2	0.904

Table 77 Sensitivity Analysis Results for Financial Cost

Finish: Green
Pinion: Reaction

Rank	Name	Regr
#1	Compressed Air Cost Rate	0.858
#2	Operator Labor Cost Rate	0.434
#3	Electrical Energy Cost Rate	0.137
#4	Bore Hone / Processing Time (min)	0.128
#5	Dry Hob / Processing Time (min)	0.112
#6	Bore Hone / Batch Size	-0.084
#7	HT Furnace / Electrical Power (kW)	0.076
#8	Bore Hone / Compressed Air (cfm)	0.052
#9	Recycling Cost Rate	0.035
#10	Water Cost Rate	0.014
	R^2	0.990

Finish: Hard
Pinion: Rear Short

Rank	Name	Regr
#1	Compressed Air Cost Rate	0.889
#2	Operator Labor Cost Rate	0.237
#3	Pre-Grind Washer / Compressed Air (cfm)	0.182
#4	Electrical Energy Cost Rate	0.167
#5	Pre-Grind Washer / Processing Time (min)	0.160
#6	Teeth Grinder / Compressed Air (cfm)	0.105
#7	Bore Hone / Processing Time (min)	0.070
#8	HT Furnace / Electrical Power (kW)	0.067
#9	Dry Hob / Processing Time (min)	0.061
#10	Bore Hone / Batch Size	-0.051
	R^2	0.959

Table 78 Sensitivity Analysis Results for Energy

Finish: Green
Pinion: Reaction

Rank	Name	Regr
#1	Dry Hob / Processing Time (min)	0.570
#2	HT Furnace / Electrical Power (kW)	0.551
#3	Bore Hone / Processing Time (min)	0.435
#4	Bore Hone / Batch Size	-0.293
#5	Bore Hone / Compressed Air (cfm)	0.177
#6	Bore Hone / Electrical Power (kW)	0.079
#7	Dry Hob / Electrical Power (kW)	0.050
#8	Final Washer / Batch Size	-0.049
#9	Material Handler / Electrical Power (kW)	0.040
#10	Face Grinder / Electrical Power (kW)	0.030
	R^2	0.948

Finish: Hard
Pinion: Rear Short

Rank	Name	Regr
#1	Pre-Grind Washer / Compressed Air (cfm)	0.481
#2	Pre-Grind Washer / Processing Time (min)	0.464
#3	HT Furnace / Electrical Power (kW)	0.409
#4	Teeth Grinder / Compressed Air (cfm)	0.284
#5	Teeth Grinder / Electrical Power (kW)	0.270
#6	Dry Hob / Processing Time (min)	0.245
#7	Bore Hone / Processing Time (min)	0.200
#8	Bore Hone / Batch Size	-0.132
#9	Chamfer / Compressed Air (cfm)	0.122
#10	Bore Hone / Compressed Air (cfm)	0.075
	R^2	0.905

These significant, uncertain inputs to the manufacturing performance estimates can be used to explain the relative widths of the performance estimate distributions. All inputs with uncertainty were modeled as uniform probability density functions because these gear production machines and processes are not yet well characterized. The measure of input uncertainty is the width or spread of the uniform pdf modeling the input; this width of the uncertainty (spread) is found by looking in the database where the uncertain input is housed, and subtracting its lower bound from the upper bound. This input spread may be normalized however by the nominal batch size, if the input item is associated with a primary machine. This normalization spreads the uncertainty of the primary machine characteristic evenly over all the production parts of a batch. This is justifiable because the manufacturing performance estimates are given on a per unit of production basis; looking at Equation 1 from Chapter 3 the batch size of a primary machine is seen to divide up the environmental burdens of a primary machine equally among all the units of production under operation simultaneously. Significant input items to manufacturing performance estimates that are not associated with primary machine operations, such as cost rates and batch sizes themselves, are 'normalized' by dividing by one; essentially these other uncertain input items may already be considered as normalized.

In Figures 118, 119, and 119 for both the green finished reaction pinion and the hard finished rear short pinion the significant inputs to the estimates of SPS, financial costs, and energy, are given, respectively, with the normalized spreads of those significant inputs' uncertainties. The original input spread and the nominal batch size are also given for each input so that the normalization process is clear. For each comparison of the green and hard finished pinion in Figure 118, 119, and 120, looking at the relative size of normalized spreads for inputs of the different gears with approximate ranks and regression coefficients will give insight into the relative size difference of the estimate distribution spreads. The significant input uncertainties to the estimation of SPS are first given in Figure 118.

Finish: Green					
Pinion: Reaction			Input	Nominal	Normalized
Rank	**Name**	**Regr**	**Spread**	**Batch Size**	**Spread**
#1	HT Furnace / Electrical Power (kW)	0.580	401.1	928	0.4
#2	Dry Hob / Processing Time (min)	0.498	0.192	1	0.192
#3	Bore Hone / Processing Time (min)	0.458	0.573	7	0.082
#4	Bore Hone / Batch Size	-0.308	6	--	6
#5	Bore Hone / Compressed Air (cfm)	0.186	15.5	7	2.2
#6	Bore Hone / Electrical Power (kW)	0.083	90.3	7	12.9
#7	Dry Hob / Electrical Power (kW)	0.053	5.1	1	5.1
#8	Final Washer / Batch Size	-0.052	39	--	39
#9	Material Handler / Electrical Power (kW)	0.042	1.7	1	1.7
#10	Face Grinder / Electrical Power (kW)	0.032	19.1	2	9.5
	R^2	0.940			

Finish: Hard					
Pinion: Rear Short			Input	Nominal	Normalized
Rank	**Name**	**Regr**	**Spread**	**Batch Size**	**Spread**
#1	Pre-Grind Washer / Compressed Air (cfm)	0.486	22.0	1	22.0
#2	Pre-Grind Washer / Processing Time (min)	0.469	0.477	1	0.477
#3	HT Furnace / Electrical Power (kW)	0.413	401.1	928	0.4
#4	Teeth Grinder / Compressed Air (cfm)	0.287	1.3	1	1.3
#5	Teeth Grinder / Electrical Power (kW)	0.273	15.7	1	15.7
#6	Dry Hob / Processing Time (min)	0.205	0.192	7	0.027
#7	Bore Hone / Processing Time (min)	0.202	0.573	1	0.573
#8	Bore Hone / Batch Size	-0.134	6	--	6
#9	Chamfer / Compressed Air (cfm)	0.123	2.6	1	2.6
#10	Bore Hone / Compressed Air (cfm)	0.076	15.5	7	2.2
	R^2	0.904			

Figure 118 Significant SPS Input Uncertainties

The reason for the much wider rear short pinion SPS estimate spread is easily explained using Figure 118. The normalized spreads of the top five significant inputs for both pinion gears are taken from Figure 118 and a relative difference calculated. The relative difference is found here by dividing the normalized spread of the hard finished pinion input by the normalized spread of the green finished pinion input; the relative differences in normalized uncertainties for SPS estimates for the different gears are given in Table 79.

Table 79 Relative Differences in Normalized Uncertainties for SPS Estimates

Rank	Relative Difference
#1	50.9
#2	2.5
#3	5.3
#4	0.2
#5	7.1

For example, the relative difference between the pinion gears, for the most significant input (ranked #1), is found to be 50.9 in Table 79 by dividing 22.0 by 0.4. The normalized uncertainty of the compressed air rate in cfm of the pre-grind washing operation is two orders of magnitude larger than the normalized uncertainty of the electrical power in kW of the heat treat furnace. This relative difference means that the uncertainty of the most significant input to the estimation of SPS for the hard finished rear short pinion gear is over 50 times larger than the uncertainty of the most significant input to the estimation of SPS for the green finished reaction pinion. The normalized spread of four of the five significant inputs to the hard finished gear SPS estimates are significantly larger than the normalized spread of the inputs to the green finished gear SPS.

Clearly this huge disparity in the relative sizes of significant input uncertainties is causing a disparity in the sizes of calculated performance estimate uncertainties. In other words, the significant inputs to the estimates of SPS for the hard finished gear have greater uncertainty, measured by the width of the uniform distribution modeling the input, than the significant inputs to the estimates of SPS for the green finished gear, and thus the uncertainty of the calculated estimates will obviously be greater. Generally, using the same mathematical model, a set of inputs with a larger degree of uncertainty than another set of inputs will have a larger degree of uncertainty in the model outputs than those outputs obtained from the less uncertain inputs.

The significant input uncertainties to the estimation of financial cost are given in Figure 119, and the relative differences in normalized uncertainties for the significant inputs to cost estimation are given in Table 80.

Finish: Green					
Pinion: Reaction			Input Spread	Nominal Batch Size	Normalized Spread
Rank	**Name**	**Regr**			
#1	Compressed Air Cost Rate	0.858	0.020	--	0.020
#2	Operator Labor Cost Rate	0.434	20.000	--	20.000
#3	Electrical Energy Cost Rate	0.137	0.040	--	0.040
#4	Bore Hone / Processing Time (min)	0.128	0.573	7	0.082
#5	Dry Hob / Processing Time (min)	0.112	0.192	1	0.192
#6	Bore Hone / Batch Size	-0.084	6	--	6
#7	HT Furnace / Electrical Power (kW)	0.076	401.1	928	0.4
#8	Bore Hone / Compressed Air (cfm)	0.052	15.5	7	2.2
#9	Recycling Cost Rate	0.035	100.000	--	100.000
#10	Water Cost Rate	0.014	0.002	--	0.002
	R^2	0.990			

Finish: Hard					
Pinion: Rear Short			Input Spread	Nominal Batch Size	Normalized Spread
Rank	**Name**	**Regr**			
#1	Compressed Air Cost Rate	0.889	0.020	--	0.020
#2	Operator Labor Cost Rate	0.237	20.000	--	20.000
#3	Pre-Grind Washer / Compressed Air (cfm)	0.182	22.0	1	22.0
#4	Electrical Energy Cost Rate	0.167	0.040	--	0.040
#5	Pre-Grind Washer / Processing Time (min)	0.160	0.477	1	0.477
#6	Teeth Grinder / Compressed Air (cfm)	0.105	1.3	1	1.3
#7	Bore Hone / Processing Time (min)	0.070	0.573	7	0.082
#8	HT Furnace / Electrical Power (kW)	0.067	401.1	928	0.4
#9	Dry Hob / Processing Time (min)	0.061	0.192	1	0.192
#10	Bore Hone / Batch Size	-0.051	6.000	--	6.000
	R^2	0.959			

Figure 119 Significant Financial Cost Input Uncertainties

Table 80 Relative Differences in Normalized Uncertainties for Cost Estimates

Rank	Relative Difference
#1	1.0
#2	1.0
#3	550.1
#4	0.5
#5	2.5

In Table 80 the first two significant inputs are seen to be equivalent for both gear cost estimates. The difference in estimate uncertainties may thus be attributed to the great relative difference of the third most significant inputs to the gear cost estimates. The normalized uncertainty of the compressed air rate in cfm of the pre-grind washing operation is three orders of magnitude larger than the normalized uncertainty of the electrical energy cost rate in $ / kWh. Additionally, the fifth most significant input to the hard finished gear cost estimate also has a normalized input uncertainty about two and a half times that of green finished gear input.

Turning to the final manufacturing performance estimate whose uncertainty differences needs illumination, the significant input uncertainties to the estimation of energy are given in Figure 120. The relative differences in normalized uncertainties for the significant inputs to energy estimation are also given in Table 81.

Finish: Green					
Pinion: Reaction			Input	Nominal	Normalized
Rank	**Name**	**Regr**	**Spread**	**Batch Size**	**Spread**
#1	Dry Hob / Processing Time (min)	0.570	0.192	1	0.192
#2	HT Furnace / Electrical Power (kW)	0.551	401.1	928	0.4
#3	Bore Hone / Processing Time (min)	0.435	0.573	7	0.082
#4	Bore Hone / Batch Size	-0.293	6	--	6
#5	Bore Hone / Compressed Air (cfm)	0.177	15.5	7	2.2
#6	Bore Hone / Electrical Power (kW)	0.079	90.3	7	12.9
#7	Dry Hob / Electrical Power (kW)	0.050	5.1	1	5.1
#8	Final Washer / Batch Size	-0.049	39	--	39
#9	Material Handler / Electrical Power (kW)	0.040	1.7	1	1.7
#10	Face Grinder / Electrical Power (kW)	0.030	19.1	2	9.5
	R^2	0.948			

Finish: Hard					
Pinion: Rear Short			Input	Nominal	Normalized
Rank	**Name**	**Regr**	**Spread**	**Batch Size**	**Spread**
#1	Pre-Grind Washer / Compressed Air (cfm)	0.481	22.0	1	22.0
#2	Pre-Grind Washer / Processing Time (min)	0.464	0.477	1	0.477
#3	HT Furnace / Electrical Power (kW)	0.409	401.1	928	0.4
#4	Teeth Grinder / Compressed Air (cfm)	0.284	1.3	1	1.3
#5	Teeth Grinder / Electrical Power (kW)	0.270	15.7	1	15.7
#6	Dry Hob / Processing Time (min)	0.245	0.192	1	0.192
#7	Bore Hone / Processing Time (min)	0.200	0.573	7	0.082
#8	Bore Hone / Batch Size	-0.132	6	--	6
#9	Chamfer / Compressed Air (cfm)	0.122	2.6	1	2.6
#10	Bore Hone / Compressed Air (cfm)	0.075	15.5	1	15.5
	R^2	0.905			

Figure 120 Significant Financial Energy Input Uncertainties

Table 81 Relative Differences in Normalized Uncertainties for Energy Estimates

Rank	Relative Difference
#1	114.8
#2	1.1
#3	5.3
#4	0.2
#5	7.1

The relative differences in input uncertainties of Table 81 are similar to those in Table 79 for SPS estimates. The normalized spread of four of the five significant inputs to the hard finished gear energy use estimates are significantly larger than the normalized spread of the inputs to the green finished gear energy use. These larger input uncertainties easily explain the wider energy estimate distribution for the hard finished pinion gear.

The bottom line of this section is that the most significant inputs to the manufacturing performance estimates of SPS, financial costs, and energy of the hard finished pinion gear have larger uncertainty than those significant inputs to the performance estimates of the green finished pinion gear, and thus the uncertainties for those manufacturing performance estimates for the hard finished gears are indeed larger than the estimates for the green finished gear.

7.8.3.2. Using Performance Estimate Uncertainties to Understand Risk

Plotting performance estimates as distributions in the manner of Figures 113 - 117 is also meant to uncover performance estimates which may overlap between the gears and / or have a spread wider than a decision maker defined acceptable risk. Additionally the spread on the deltas (i.e., the differences) between performance estimates may be found. For example, looking at the difference in energy use in Figure 117, the nominal difference between the hard finished rear short pinion and the green finished reaction pinion is about 5 kWh / gear. However, with knowledge of the spread of the energy use estimates for both pinion gears, it is seen that the energy difference is as small as about 2 kWh / gear, or as large as about 9 kWh / gear, though these values only occur at very small probability. Especially if the difference were to approach the low end, and the low end difference approaches zero, a risk-averse decision maker may become inclined to consider the difference in the estimates statistically insignificant. The range in deltas in the comparison between manufacturing performance indicators for the hard finished rear short pinion gear and the green finished reaction pinion gear are given in Table 82; the indicators presented are those plotted in Figures 113 - 117 above that have no overlap.

Table 82 Delta Ranges for Indicator Estimates

	Nominal	Minimum	Maximum	units
Environmental SPS	156	53	281	mpt / part
Financial Cost	0.94	0.08	1.82	$ / part
Water Use	1.5	0.7	3.8	gal / part
Energy	4.9	1.5	9.0	kWh / part

Except for recyclable material and water there is no overlap between performance indicator estimates, thus demonstrating statistically significant difference between most of the estimates, which are of course predicated on the inputs from the machine databases, which may or may not be wholly representative of reality. The overlap region for water use is highlighted in Figure 115; though there is some overlap, the probability of this occurring is incredibly small, as the overlap is in the tail region of the green finished reaction pinion. Recyclable material generation, shown in Figure 116, overlaps highly as expected due to the similarities in the gear size and design, and thus the amount of material removed by dry operations, which is assumed to be wholly recyclable.

The implications on decision making for an overlap situation depends on the risk-averseness of the decision maker and the extent of the overlap; where it is not excessively expensive to do so, machine information which feeds the overlapping estimate calculation should be improved and / or verified. Knowledge of these risks allows a level (or lack) of statistical confidence to be built on estimates and differences, and allows more informed decision making versus simply using the deterministic results of Table 69 blindly.

Now that the cost and environmental performances of actual transmission pinion gear manufacture by two different methods has been analyzed using the tool developed in this thesis, the tool is applied in a predictive fashion to a situation in an early stage of product design where little information on the process design and operation exists. The strength or certainty of making a decision to design gears for a green or hard finishing process will be examined.

7.9. At Conceptual and Early Embodiment Stages of Product Design

The previous analyses of cost and environmental performances of gear manufacture were more backward looking; that is, existing production lines in a plant facility were analyzed and manufacturing performances assessed. These were a demonstration of the developed tool and method as manufacturing performance estimator or accounting system, which may possibly be used to support cost and environmental conscious in manufacturing related decision making processes. In this example however an early stage of *product* design will be assumed. In an early stage of product design, such as conceptual design or early embodiment design, per the design methodology of Pahl and Beitz (Pahl, et al. 1996), very little or no information is known on the process design to produce the part being designed. In fact process design or planning will "lag" product design somewhat because it requires the product design to be substantially narrowed and well defined. The implications of this assumption are the following: (1)

cost and environmental performance estimates need to be generated when a process design is not well established, (2) the sharing of both primary and auxiliary production machinery is not considered, (3) multiples of machinery necessary to achieve proper line balance and throughput is not considered, and (4) differing numbers of pinion gears that may be in the planetary gear sets of a transmission is not known. As a result of the preceding, simple process plans are generated whereby one of each primary and auxiliary machine is employed, and the number of pinion gear types is assumed to be constant, here it is three. That is, for three planetary assemblies in one transmission, there are three pinion gears in each assembly.

Essentially, this example simulates the situation where a product designer wishes to get early, first pass feedback information on manufacturing performance for making a tolerancing decision. Specifically for gear design, this is the situation where a gear designer, in early product design when design changes are still possible, wishes to know the implications on manufacturing cost and environmental performance for specifying gear feature tolerances such that hard finishing may be required over the preferred and base method of green finishing.

Without any sharing of primary and auxiliary production machinery, and no knowledge of the numbers of machines required for line balance and throughput, determining the numbers of machines and the auxiliary hourly production rates are trivial exercises. Using the same assumption from the previous example on transmission volume per year, 450,000, and facility working hours the required hourly production rate is found to be 80. The auxiliary hourly production rate is simply that of the primary production process; for a pinion gear production line this rate is 240 per hour. The hourly production rates of the auxiliary machinery for a ‘simple’ gear production line are given in Table 83.

Table 83 Hourly Production Rates

Hourly Production Rates	
Dust Collector	240
Mist Collector	240
Coolant System	240
Material Handler	240
External Loader	240
Pinion Lines	240
Other Gear Lines	80

The values contained in Table 83 may be contrasted to those in Tables 44 and 45, and 58 for real gear production processes where auxiliary machinery supports multiple production lines simultaneously. The values in Table 83 are significantly smaller than those in the other tables, a fact which will cause the environmental burdens and machine costs to be spread over fewer production gears and thus increasing both the financial costs and environmental impacts per gear.

Again, sharing of either primary or auxiliary production machinery is neglected, because the complex interactions and sharing of production machinery among the other gearing production lines of a transmission is wholly unknown. As the product design progresses and becomes more well defined, the process plan will begin to take shape and sharing of machinery and quantities of machinery will become clearer. Additionally, if past production knowledge exists, a previous process plan may be used as the model or template for laying out a simple, early product design stage process plan. Here it is assumed previous process plans are unknown; thus the number of production machinery and sharing of that machinery is unknown and the setting of numbers and fractions is unnecessarily arbitrary. The only approach to circumvent this is to set the number of machines for each major processing step to one; material handling machinery may be estimated based on the number of machine-to-machine WIP transfers required. The primary and auxiliary machinery of simple green and hard finished pinion gear processes are given in Table 84.

Table 84 Simple Green (left) and Hard (right) Finished Pinion Process Machines

	Green Finish Process	
Primary	Dry Hob	1
	Roll	1
	Pre-HT Washer	1
	HT Furnace	1
	Face Grinder	1
	Bore Hone	1
	Burnisher	1
	Final Washer	1
Auxiliary	Dust Collector	1
	Mist Collector	1
	Coolant System	1
	Material Handler	7
	External Loader	2

	Hard Finish Process	
Primary	Dry Hob	1
	Chamfer	1
	Pre-HT Washer	1
	HT Furnace	1
	Face Grinder	1
	Bore Hone	1
	Pre-Grind Washer	1
	Teeth Grinder	1
	Final Washer	1
Auxiliary	Dust Collector	1
	Mist Collector	1
	Coolant System	1
	Material Handler	8
	External Loader	2

With the types and quantities of machines, and the auxiliary hourly production rates specified, the developed tool may be used to generate manufacturing cost and environmental performance estimates using the procedure previously explained. The manufacturing performance estimates for the simple green and hard finished pinion gear processes are presented in Tables 85 and 86. The per-gear results of the uncertainty analysis are presented, with the mean (μ), standard deviation (σ), minimum, and maximum, along with the units for each indicator.

Table 85 Simple Green Finished Pinion Process Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	189	16.8	143	238	mpt / part
Financial Cost	1.15	0.109	0.87	1.45	$ / part
Water Use	4.2	0.36	3.7	5.9	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.09	0.018	0.06	0.13	lb / part
Special Waste	0.00	0.000	0.00	0.00	lb / part
Energy	6.0	0.54	4.6	7.6	kWh / part
CO2	8.07	0.715	6.16	10.18	lb / part

Table 86 Simple Hard Finished Pinion Process Environmental and Cost Performance Estimates

	μ	σ	Min	Max	Units
Environmental SPS	243	25.7	181	327	mpt / part
Financial Cost	1.45	0.150	1.09	1.98	$ / part
Water Use	4.2	0.36	3.7	5.8	gal / part
Landfill Waste	0.00	0.000	0.00	0.00	lb / part
Recyclable Material	0.10	0.018	0.07	0.13	lb / part
Special Waste	0.09	0.003	0.09	0.10	lb / part
Energy	7.8	0.81	5.8	10.4	kWh / part
CO2	10.38	1.089	7.73	13.92	lb / part

Looking at the standard deviations in Tables 85 and 86 it is seen again that the standard deviations of the manufacturing performance indicators of SPS, financial cost, and energy are different between the two types of pinion gears; the standard deviations of the indicator estimates for the hard finished pinion are larger than those of the green finished pinion which is indicative of a wider spread or greater uncertainty of the particular performance estimates. The different sizes of standard deviations for SPS, financial cost, and energy between the two pinion gears may be explained by the same discussion presented in the previous section. Essentially the significant inputs to those indicator estimates for the hard finished pinion gear have a larger degree of uncertainty than those significant inputs of the green finished pinion gear.

The Monte Carlo simulations iterated hundreds of times in each analysis. Given the uncertainty of machine information in the databases, knowledge of the resulting uncertainty in performance estimates is critical. As a caveat, the lack of information for some items in the machine databases must be factored in to decision making; an estimate of zero for an indicator does not necessarily mean that there is zero of that item. Using the deterministic results from the tool, a comparison of the two gears' performances in their manufacture is given in Table 87.

Table 87 Comparison of Environmental and Cost Performance Estimates for Simple Pinion Processes

		Hard Finish	Green Finish	units
Main	Environmental SPS	242	187	mpt / part
	Financial Cost	1.45	1.15	$ / part
Inventory	Water Use	4.2	4.1	gal / part
	Landfill Waste	0.00	0.00	lb / part
	Recyclable Material	0.10	0.09	lb / part
	Special Waste	0.09	0.00	lb / part
	Energy	7.7	6.0	kWh / part
	CO2	10.32	8.01	lb / part

The hard finished pinion gears are still performing worse than the green finished gears, though it is less overwhelmingly so. The relative differences for environmental

SPS, financial cost, along with energy use and CO_2 generation for hard finish over green finish are no longer double; the relative differences are much more modest at about 1.25 to 1.30. Water use and recyclable material generation are practically the same for both pinion gear finishing methods; recyclable material is expected to exhibit this behavior due to the similarity in gear design and size, as previously discussed. Special waste is significantly different, again. Also, as discussed previously, the estimates of zero for landfill waste for the two pinion gears are suspect. The amount per gear is miniscule, and does not show up with three decimal places, and the landfill waste generation rates are not adequately known for the machinery in these processes. The relative differences in performance estimates for these early product design phase hard and green finished pinion gears are given in Table 88.

Table 88 Relative Difference in Performance Estimates

	Relative Difference
Environmental SPS	1.29
Financial Cost	1.26
Water Use	1.01
Landfill Waste	--
Recyclable Material	1.01
Special Waste	579.13
Energy	1.29
CO2	1.29

In addition to knowledge of the mean and standard deviation of the performance indicators, the minimum and maximum values are noted. Using these values and assuming normal distribution of the performance indicators, plots are generated of the shape of each estimated indicator to facilitate comparisons. The x-axis is the value of the estimate, and the y-axis is the probability of realizing that estimate value; integrating under the curve will yield a value of 1. Comparisons of the hard finished pinion gear and the green finished pinion gear are made in the following figures with overlap regions highlighted; environmental impact score in Figure 121, financial cost in Figure 122, water use in Figure 123, recyclable material in Figure 124, and energy use in Figure 125. Landfill waste is not plotted because its estimate is zero for both gears, special waste is not plotted because the estimate is zero with no uncertainty for the green finished pinion gear making a comparison trivial and uninteresting, and CO_2 is not plotted because it matches identically the energy plot.

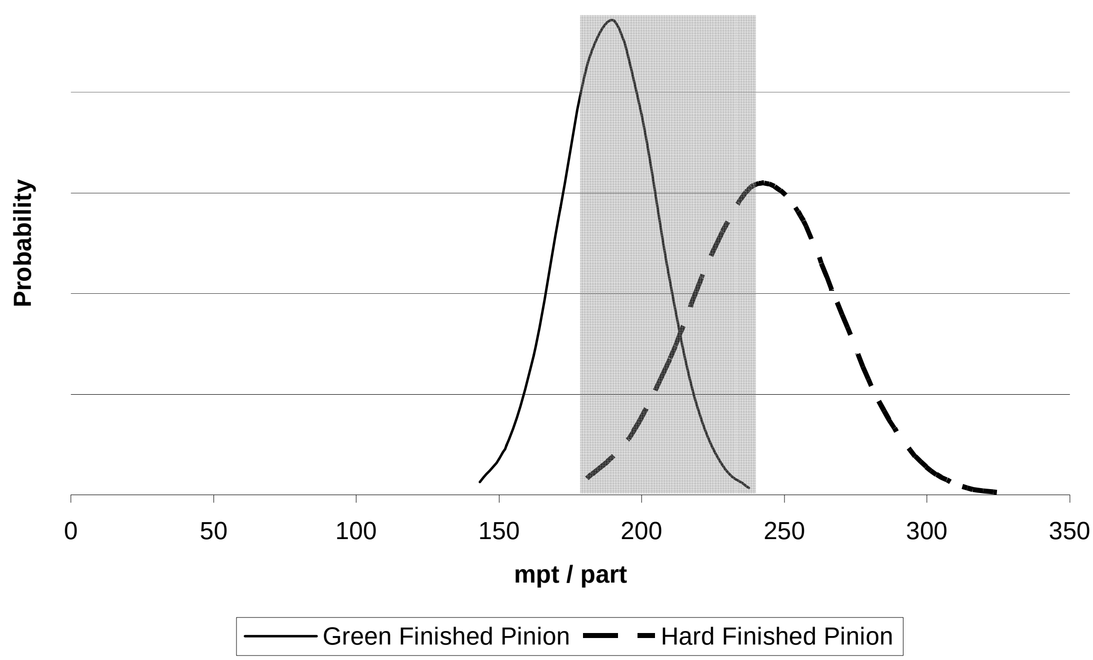


Figure 121 Environmental Impact Score Comparison

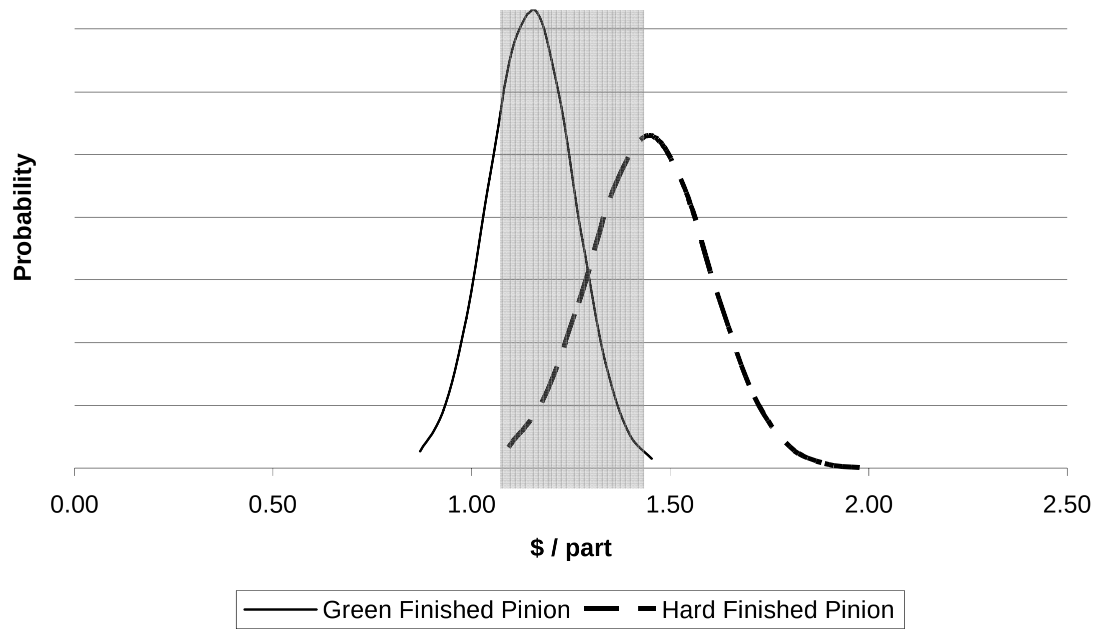


Figure 122 Financial Cost Comparison

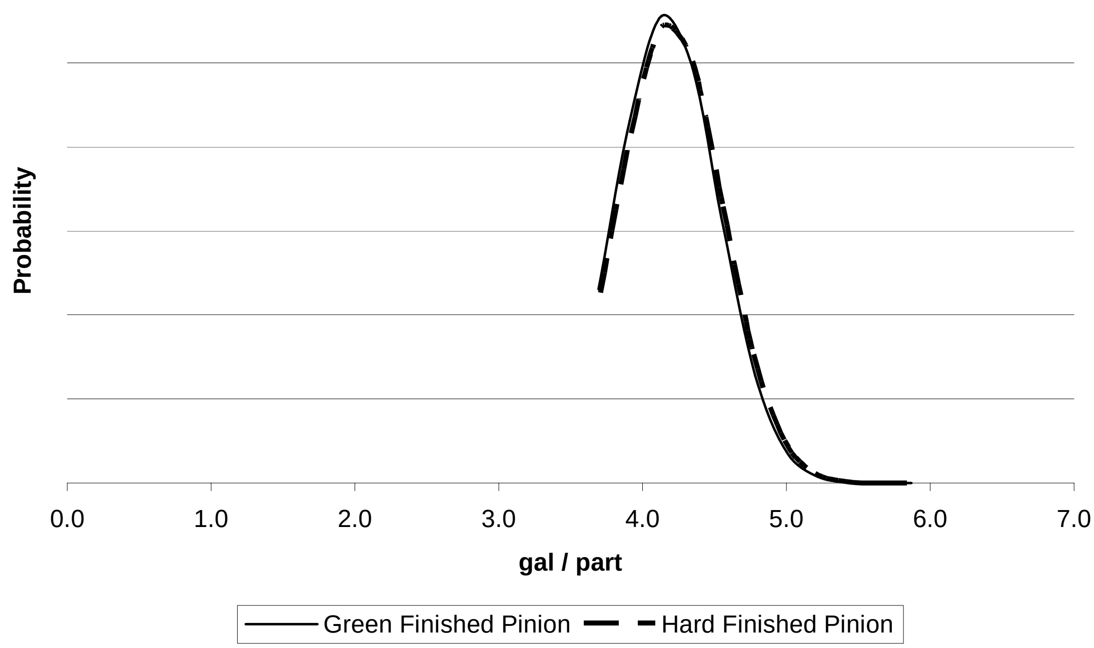


Figure 123 Water Use Comparison

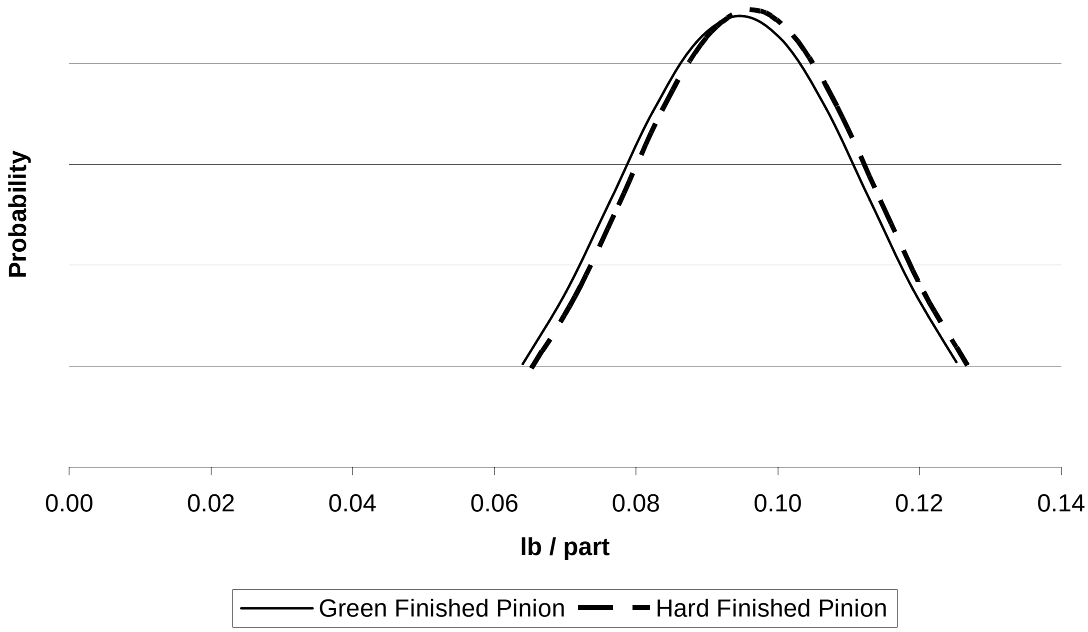


Figure 124 Recyclable Material Comparison

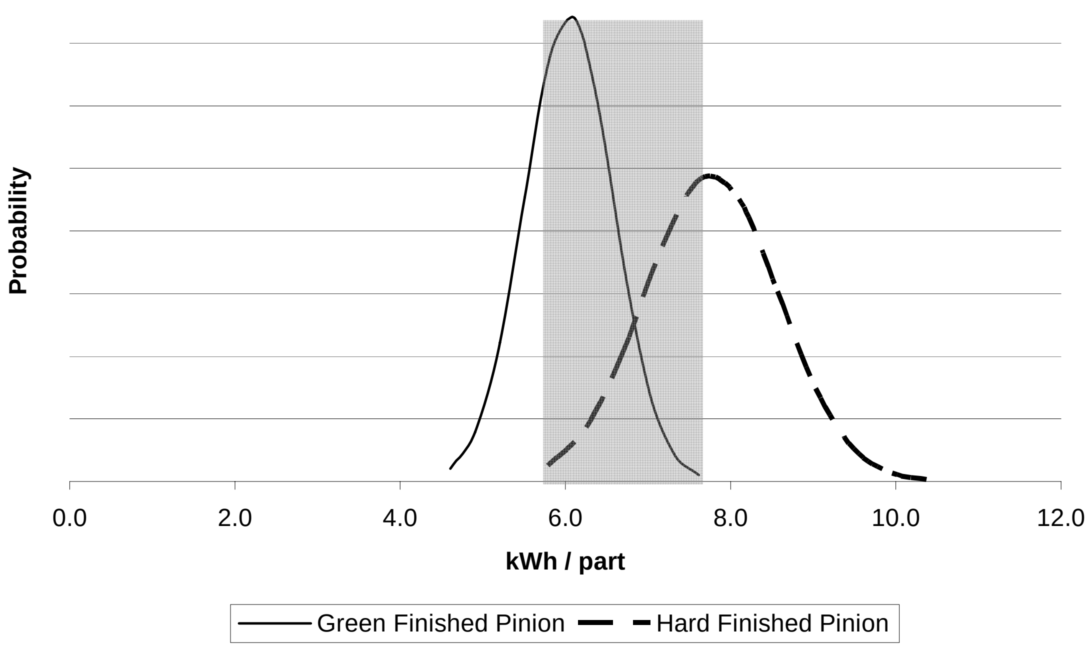


Figure 125 Energy Use Comparison

The numbers of machines, machine fractions, and auxiliary hourly production rates could also be modeled as uncertain and / or variable and included in uncertainty analysis, if some historical information on similar processes exists. Varying the quantities of machinery in uncertainty analyses will yield non-linear results, as ‘jumps’ may be expected by the addition or subtraction of a discrete number of machinery. Sharing of machinery and ensuing machine fractions, as well as auxiliary hourly production rate though are more continuous, but could still have significant effects on performance estimates by spreading the performance of production machinery over more units of production.

The implications on decision making for an overlap situation depends on the risk-averseness of the decision maker and the extent of the overlap; where it is not excessively expensive to do so, machine information which feeds the overlapping estimate calculation should be improved and / or verified. Knowledge of these risks allows a level (or lack) of statistical confidence to be built on estimates and their differences, and allows more informed decision making versus simply using the deterministic results of Table 87 blindly. The extent of overlap in comparing these simple green and hard finished pinion gears is much greater than the overlap seen in the comparison of the two actual production processes for green and hard finished pinion gears. The main finding of this last example of an early product design situation, is that the hard finishing of pinion gears is still more ‘expensive’, with decreased manufacturing cost and environmental performance, over a green finishing pinion process according to most of the defined indicators, though less overwhelmingly so.

7.10. Thesis Roadmap

In this chapter the design and ensuing manufacturing performances (cost and environmental) of automotive transmission pinion gears were discussed and the tool developed in this thesis applied. The motivation for analyzing manufacturing performance was established by discussing the effects of design of automobiles and their components on the environment. Also, gear tolerances and design, and their implications on noise, vibration, and harshness (NVH), a key automobile performance characteristic, as well as an overview of gear manufacturing methods was given. The feature tolerances design of the pinion gears from two transmissions were classified according to the AGMA and DIN quality classifications, and the quality numbers used to predict the difference in cost to manufacture the different pinions.

Two common methods for producing transmission gearing with differing tolerance design specifications were each analyzed using the developed tool. Green finishing, a preferred method of gear manufacture, produces gears with greater variation in gear geometry features, while hard finishing is able to achieve more accurate gear geometries by 'finishing' the gears post-heat treatment hardening, which introduces distortion. Actual gearing production data and information provided the basis of these assessments and comparisons. The chapter finished with an example of an early design phase performance prediction when very little process information is known.

The Excel-based tool developed has been exercised by two illustrative examples of increasing complexity in Chapter 6 as proof of concept and utility of the method, and partially proved the Empirical Performance Validity of the proposed method. A study of automotive transmission pinion gear manufacture, where gear tolerancing decisions have significant manufacturing environmental and cost performance implications, has been conducted in this chapter to give further evidence of Empirical Performance Validity. The thesis now closes with a Critical Evaluation, of this work in Chapter 8, including a discussion of Theoretical Performance Validity, and a Closure with final remarks in Chapter 9.

CHAPTER 8

CRITICAL EVALUATION

In this chapter a critical evaluation of the method proposed in this thesis for estimating the cost and environmental performances of manufacturing processes required to achieve specific product designs. The efforts to validate this method with the two example problems of Chapters 6 and 7 will be discussed using the framework of the Validation Square, introduced in Chapter 1. The shortcomings of the method that have been identified, additional work needed, and what has been achieved in this proposed method, will all be addressed. Remembering that the objective of this thesis was to develop a method for quantifiably relating product tolerancing decisions to environmental and cost performances in manufacturing in order to provide decision support for cost and environmentally conscious design for manufacturing, the discussion of validation will thus be geared towards that of the *method* itself, and not the numerical results of the two examples, per se. While the examples are interesting on their own, the focus here has been on developing the method and tool with which to conduct such analyses in a novel manner superior to the existing available methods for estimating performance in manufacturing, for use as design decision support. Validation of the method is attempted by addressing each of the regions in the Validation Square, and instilling enough confidence in each block to enable a leap of faith to Theoretical Performance Validity, the ability to achieve useful results from the method beyond the example problems.

8.1 Critical Evaluation of Validation

Recalling the Validation Square introduced in Chapter 1 as the construct for validating the method proposed in this thesis, it is again pictured in Figure 126, and brief explanations of each of the regions follow.

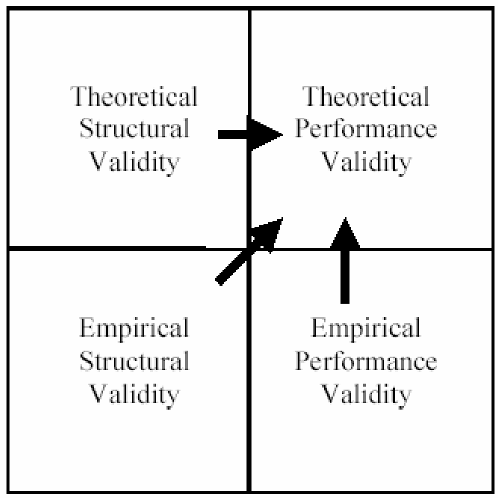


Figure 126 The Validation Square

Theoretical Structural Validity deals with the internal consistency of the design method and the constructs within it, and its logical soundness as a whole. Empirical Structural Validity is the appropriateness of the example problems that have been used to test the method. Empirical Performance Validity is the ability of the method to produce appropriate results for the chosen example problems. The last region of the Validation Square is Theoretical Performance Validity, the ability for the method to produce results for applications beyond the chosen example problems. This last region cannot be proven explicitly or empirically; it must be assumed based on the success of the proposed method for each of the other regions and the method's ability to produce useful results over a broad range of applications. In the following sections the performance of the method proposed in this thesis in each of the regions of the Validation Square is discussed. The discussion of each region is kicked off by posing its appropriate question.

8.1.1. Theoretical Structural Validity

Does each of the steps in the method make sense by themselves and do the steps fit together in a logical manner?

This question is addressed in Chapters 3 and 4 of this thesis. The development of the method, including the many details and workings of the method are found in Chapter 3. In Chapter 4 the key method components, the databases including their population and features, are fully discussed. The flow of processing steps in the method follows an ordered and logical path from the inputting of a part with its feature designs in the front end, to the performance estimates outputted from the back end process accounting. Before estimating the manufacturing performance of a part, that manufacturing process to achieve that part must be established. The front end and back parts of the method may operate independently of one another however; the front end may be used for simple process planning by filtering the available primary process machines by their capabilities, and the back end may be used as a process accounting tool for estimating the manufacturing performance of a process whose machinery operating characteristics are captured in databases. This object-oriented nature of the method's working requires ordered and well defined inputs to and outputs from each of the method's halves. The steps in the method follow a very similar path to the methods proposed by Ou-Yang and Lin, and Shehab and Abdalla (Ou-Yang, et al. 1997, Shehab, et al. 2001) to predict costs in part manufacture to support concurrent design, discussed in Chapter 2. Others have found following methods similar to that proposed in this thesis useful and valid in their research, and thus some measure of credibility may be ascribed to the method proposed here. The use of knowledge bases, repositories, or databases of past manufacturing knowledge, data, and information is fairly well accepted for gauging potential and likely future performances of manufacturing operations.

8.1.2. Empirical Structural Validity

Are the example problems appropriate?

The example problems used to test the method are given in Chapters 6 and 7 of this thesis. The illustrative examples with the simple machined parts and also the study of automotive transmission pinion gears are both appropriate examples to test this method for the following reasons: (1) both are high volume machining-based manufacturing operations which require additional auxiliary machinery to support the primary processing of parts, (2) there are steady state mass and energy flows into and out of the manufacturing processes in both examples which need accounting to fully and rigorously ascertain their quantities, costs, and impacts on the environment, and (3) changes in the parts' feature design tolerances have direct bearing on both the selection and operation of the respective manufacturing processes. The illustrative examples of Chapter 6 are hypothetical and simplistic, but they exercise the method in order to establish a proof of the concept and also demonstrate the potential benefits to be gained in using the method, albeit in an idealized and simplified situation.

The establishment of Theoretical and Empirical Structural Validities is fairly straightforward and has been accomplished here with a fairly high degree of confidence. These regions are perhaps the easiest to achieve, as the focus is decidedly inward looking (navel gazing) and detail oriented in a somewhat isolated development environment. Establishing Empirical and Theoretical Performance Validities, discussed in the next sections, is harder to accomplish as the previously protected nascent method is exposed to the harsh realities of actual use and application, and will begin to break down and confidence diminished. The difficulties and shortcomings of the method, and the usefulness of it and results generated from using it, however must be disclosed in the spirit of academic honesty and integrity.

8.1.3. Empirical Performance Validity

Are useful results realized for the example problems?

The example problems and the results from the proposed method are given in Chapters 6 and 7. In this region of the Validation Square, the usefulness and accuracy of the manufacturing performance estimates will be discussed. To answer the overarching question of method validity, the validity of the numerical results must also be established. All the caveats necessary in interpreting the outputted performance estimates, and known weaknesses and boundaries warrant discussion.

The usefulness of the estimates from the illustrative examples are suspect; the data to fully fill the machine databases in Chapter 6 is hypothetical and somewhat contrived, though as realistic as possible. Given this situation no conclusions or generalizations may be drawn from these results related to a main question of this thesis, "What is the quantified effect of product feature tolerances on cost and environmental performances in manufacturing?" With realistic, though hypothetical, environmental burden rates, machine costs, process capabilities, and operating parameters feeding the proposed, and as yet not validated, mathematical models there is no means for checking that generated performance estimates match reality for this example. The simple mathematical models in the back end process accounting additionally have not yet been fully validated; their simplicity and reasoned derivation though lend them some degree of confidence in their validity.

The usefulness of the estimates from the study of transmission pinion gears are also suspect; the databases of gear machinery contain a large degree of uncertainty and incompleteness. Thus estimates generated in this example may only be considered as preliminary, as future data gathering and uncertainty reductions could potentially alter performance estimates significantly. At this point however, for manufacturing cost performance at least, the trend in cost difference predicted using the method is highly confirmed by the cost prediction using the gear classification schemes of AGMA and DIN. The correctness of the performance estimates has proven difficult to validate and verify given the early stages of the production programs for the gearing from the two automatic transmissions studied. As the production ramps up and reaches steady state, machine operation may be better characterized and the machinery databases updated, thus likely improving the accuracy of performance estimates. At that time the accuracy and validity of performance estimates may be better gauged; however, this time frame is beyond the scope of this research.

A key component of the method, process planning in the front end, was not fully exercised and the validity of its inclusion in the method not yet fully established. The front end process generation must be conducted to establish the potential manufacturing process required to achieve an inputted part's feature designs. Without this key link in the method, there is no direct connection from the product design, chiefly of interest are the feature tolerances, to the accounting of the manufacturing performance. The usefulness of the method to connect and relate product feature tolerances to the relatively far away end effects of manufacturing performance is diminished if the method is simply used as an accounting system for manufacturing operations. In Chapter 6, only simple part feature designs were examined, and the effects of varying tolerance levels on part feature design and resulting process planning and selection discussed. The process planning of complex was not sufficiently examined, particularly those parts on which multiple manufacturing operations affect common features, and the resulting, finished part tolerances are influenced by the stack up of variation introduced by each processing step. In Chapter 7, the transmission pinion gears discussed are mechanical components with very complex geometries, but the production processes required to achieve gears with different feature tolerances was known a priori and not generated using this method. The weakness of the method with respect to process planning is addressed in the later section on shortcomings.

The focus has clearly been on developing the structure of the method, but not all of its aspects have been adequately proven in the two examples of this thesis. Useful estimates for cost and environmental performances in manufacturing were generated, but there are caveats associated with them that thus degrade the instilled confidence of the method in the Empirical Performance Validity region of the Validation Square. These items however do not appear to be fatal flaws and may be addressed as future work and further application of the proposed method. The ability to make the leap of faith to Theoretical Performance Validity, the goal of developing most methods is discussed next.

8.1.4. Theoretical Performance Validity

Can useful results be realized for applications beyond the chosen example problem?

A short answer to this question is that most likely useful manufacturing performance estimates may indeed be realized in other design and manufacture situations. Where production processes are replicated and databases are completely populated and maintained with accurate and up-to-date data and information, including the uncertainty and variability, on process capabilities, environmental burden rates, machine costs, operating parameters, cost rates, Eco-Indicator 99 values, and facility parameters, highly accurate manufacturing performance estimates will be generated using this method. Where some manufacturing production knowledge exists in the product design community, the weakness of the method related to process planning may be alleviated somewhat; typically product designers are not wholly ignorant of the methods of producing their product designs, and the simple guidance the method provides in the selection aspects of process planning will be useful. Expanding the application of this method to other products and manufacturing processes will further support the Empirical Performance Validity, and thus while also building on the Theoretical and Empirical Structural Validities, instill greater confidence in the method and minimize the risks involved in making the leap of faith to Theoretical Performance Validity.

No method is perfect or limitless in its scope, and thus probing for the boundaries and determining validity within that space is critical for the application and use of a method. Given the confidence established in Theoretical and Empirical Structural Validity regions of the Validation Square, and the guarded confidence, with known areas for future work, established in the Empirical Performance Validity region of the

Validation Square, it is safe to expect useful results, and thus Theoretical Performance Validity, from using the method proposed in this thesis in other areas of application.

8.2 Achieved

The key achievement of the method proposed in this thesis is a method for quantifiably relating product tolerancing decisions to cost and environmental performance in part manufacture. Manufacturing performance estimates are generated by first creating the potential process required to achieve the inputted part design, and the accounting that process using machine data and information housed in databases and simple mathematical models. Knowledge of these manufacturing performance estimates may be used in the design of products to better support part feature tolerancing decisions. Clearly this would be beneficial and significant savings may be realized by enabling product designers to make better tolerance design decisions. This method may be further used within optimization procedures to set part feature tolerances and / or select production machinery given goals for manufacturing cost and environmental performances.

The strength of the proposed method however is in accounting a manufacturing process flow, modeling its inputs and outputs, and then generating indicators for cost and environmental performance. This process flow accounting may be used in a predictive fashion to support manufacturing cost and environmental performance goals in upfront product design, or in backward looking assessments of the manufacturing performances of existing production lines. Another potential use of the method is as a manufacturing decision support tool – new or alternative technology selection / evaluation, modeling potential process designs (macro and micro level) and evaluating them

The economies of scale in high volume manufacturing afford the opportunity to make significant savings (i.e., improvements) in terms of cost and environmental performance when small, incremental changes are made. For example, under the assumption from Chapter 7 that 450,000 transmissions are produced per year, with three of a particular pinion design per transmission, there will be 1.35 million pinion gears produced in a year. If only 1 kWh of energy, $0.05 in financial cost, and 1 lb of landfill wastes are reduced per each pinion gear produced, the savings realized would be 1.35 MWh reduction of energy, $67,500 savings in financial cost, and 675 tons of wastes not sent to landfill in a full year of production! These are significant values. Assuming there are three planetary gear sets per transmission, with three pinion gears per planetary gear set, the number of pinion gears produced per year for assembly into this transmission is 4.05 million gears. Considering the previously mentioned reductions in energy use, financial cost, and landfill waste are applicable to these other pinion gears as well, the cost and environmental performance improvements grow even further. The savings realized for all the pinion gears in the transmission per year of production are thus 4.05 MWh energy reduction, $202,500 savings in financial cost, and 2,025 tons of wastes not sent to a landfill. Further considering that a pinion gear is but one of thousands of components which make up one fully assembled automobile, which is but one of the millions of vehicles produced by automakers worldwide annually, incremental improvements in both manufacturing cost and environmental performances may yield incredible savings.

With this method, and the manufacturing performance estimates it generates, the opportunity to quantifiably consider these small, incremental changes in part manufacture, and thus realize tremendous savings for the company, by making more informed design decisions, is very real.

To wrap up the discussion on the achievements of the proposed method, the Requirements List from Chapter 3 will be revisited. The purpose of the Requirements List was to guide the development of the method and its implementation as an Excel-based tool, and also provide a suitable metric for measuring the performance of the end result of the developed tool. The Requirements List for the method is given again in Figure 127; following the figure a brief discussion on each item on the requirements list and how it has been addressed, and to what degree, is given.

Problem Statement		
		For a design tool to predict environmental burdens and costs in the manufacture of machined components, what features and abilities are needed/required?
No.	D W	Requirements
		Accuracy
1	D	Provide reasonably accurate first pass environmental and cost information to support design decisions
2	W	Offer capability to input information to improve accuracy of results
3	D	Incorporate uncertainity of information and data and show uncertainty in output results
		Ease of Use
4	W	Do not add significant amounts of time or tasks to product designers' workload
		Flexibility
5	D	Be flexible to accommodate new or updated process information (e.g., machines, capabilities, operating characteristics, costs, by-products, utilities, etc.)

Figure 127 Method Requirements List

1. **Provide reasonably accurate first pass environmental and cost information to support design decisions**

In relatively early phases of product design, when process plans are not defined, the use of historical production machinery and process information may be used to generate initial manufacturing performance estimates. In this method this information is stored in machinery databases, though the accuracy of the manufacturing performance estimates is only as good as the data contained in the databases. In Chapter 7 in the study of transmission pinion gear design and manufacture, real gear processing machinery data is used in situations where gear production processes are and are not well defined. In both situations the resulting difference in manufacturing performance is estimated for gears with differing tolerance designs. This information may be useful in understanding the order of magnitude or ballpark of the 'costs' associated with particular designs, and highlight feature designs that are expensive, in terms of both the environment and financial costs, and the opportunity to make design changes still exists. The achievement of this requirement has not been fully met yet due to the fact that gauging the accuracy of performance estimates generated by this method has not yet been done. This is the same issue as that discussed previously involving the difficulties and challenges associated with validating and verifying model and method outputs.

2. Offer capability to input information to improve accuracy of results

As product and process designs progress, both become more well defined. With this increased definition, a better picture of the manufacturing process required to achieve the part design develops, and more representative information can be inputted to improve estimate accuracy. In the Excel-based tool, the 'slots' where updated information may be inputted are well defined; of particular note, number of machines, machine fractions resulting from sharing of machinery, batch sizes, processing times, and auxiliary hourly production rates all will become better known as the process design progresses, and may be directly inputted into the slots of the tool. This requirement has been successfully met.

3. **Incorporate uncertainty of information and data and show uncertainty in output results**

Ignoring the uncertainty and variability of input parameters, and computing performance estimates in a deterministic fashion, strips the user of the knowledge of the possible variability in the manufacturing performance estimates and the risks involved with making decisions based on those estimates. A process is not strictly deterministic and some insight into the uncertainty of the results is necessary. In this method @RISK software for Excel was employed to conduct uncertainty analyses; uncertain and variable inputs are modeled using probability density functions, and Monte Carlo simulation conducted to generate histograms and descriptive statistics for the indicator values for cost and environmental performance of a manufacturing process. This requirement has been successfully met as well.

4. **Do not add significant amounts of time or tasks to product designers' workload**

In other words, the tool should be easy and efficient to use. A tool that is inefficient, difficult to use, and / or has a steep learning curve most likely will not be used to the degree that is desired because of its burdensome use. Using Excel, a common and well known software, is a major plus towards meeting this requirement. Additionally, the coding of macros to automate as much of the method as possible is meant to ease the tool's use by a product design user. However, the fact that process planning still requires significant user knowledge and input could be a significant strike against the ease of use by a product design user. Also, there will be some learning curve associated with learning to use the Excel-based tool, but this is to be expected with any engineering software. This requirement, though not overwhelmingly so, has been fulfilled.

5. Be flexible to accommodate new or updated process information

Different production processes may use different utilities and / or generate different by-products; a user is able to add specific environmental burdens of interest to the databases and inventory calculations of the Excel-based tool. Additionally, process characteristics such as processing times, operating costs, and environmental burden rates, change with the implementation of new technologies, improved efficiencies, upgrades, cost inflation and fluctuations, and between machine manufacturers. A user has access to and may input the 'best' available information into the various databases of the Excel-based tool. This requirement has been successfully met as well.

Given the performance of the method against the metrics of the requirements list, this method is likely to be valuable and helpful to product designers and process planners attempting to include cost and environmental consciousness in decision making efforts related to the manufacturing phase of product life cycles.

8.3 Shortcomings of Method

There are of course shortcomings of the method proposed in this thesis for estimating cost and environmental performances for the manufacturing processes required to achieve product designs. It is important to clearly state what a method can and cannot do, and illumine the boundaries of its application. The shortcomings to be discussed are related to process planning steps in the front end of the tool, databases, and computer implementation.

Process planning and generation of the front end of the method is not perfect due to its difficulty to conduct and further to automate. The method and its implementation in Excel offer the ability to guide selection decisions in process planning but not the compromise decisions; in other words, selecting the manufacturing process and the machinery for that process is included, but the tweaking of the operation of that machinery is not. Manual input is still required to make actual selection decisions in process planning, and in the setting of machine and process parameters. This situation highlights the main weakness of the method: process generation requires (significant) user input and knowledge. The tool acts as a guide only, and process generation is not fully automated, hurting the performance of the method given the item on the Requirements List stipulating that the method be as easy to use as possible for a product design user. However, automating process planning is not easily accomplished, given that process planning is more of an art than a science. The process planning operation in the method also does not address process sequencing, the specification of the proper order of manufacturing operations. Instead, manufacturing operations are simply pooled and their aggregate performances estimated. Sequencing is an important component of process planning, especially when the additive effects of multiple operations on the same features are considered. For complex parts, such as gears, sequencing of the processes and the resulting tolerance stack ups on important features can not be ignored. Process planning in the proposed method is limited to simple parts with fairly straightforward production operations. Despite the lack of automating process planning, it may still be carried out manually or with the aid of some other CAPP tool, and the back end process accounting still effectively employed.

The machine databases are perhaps the most important components of the proposed method. However, like the other methods proposed for predicting manufacturing costs, the methods break down when historical data is not available or does not exist. The same limitation is in place in this proposed method; new, novel, or innovative product designs and manufacturing processes on which no previous production machine data and information exist will cause problems when attempting to predict manufacturing performances using this method. Additionally, not addressed here, there are questions and tasks related to populating and maintaining the machine databases; where should they be located? And whose responsibility is their upkeep? In a large manufacturer these organizational and personnel issues are not insignificant.

The computer implementation of the method as a VBA powered Excel-based tool has its weaknesses as well. Lists and arrays in the Excel tool are not dynamically sized, though they are sized quite large to accommodate far more inputs than are to be seen in practice. Conducting the Filtering operation in the front end process generation does not work well for complex parts; there are difficulties in dealing with multiples of feature types and each feature must be inputted individually in the filtering of available primary machines. A key way to improve the accuracy of performance estimates is the use of correct processing times for a machine's operation; the calculation of processing times is not automated in this method, as it is in others, and must be done manually. Another item incorporated in the methods of other for predicting manufacturing costs, is an interface with a CAD system that is not present in this method. While potentially powerful, especially given the parameterized, and thus easily modified, features in a CAD part model, there are concerns related to simplicity and ease of use. The link between the part feature designs and the feedback, manufacturing performance estimates is not automated; rather, a human designer must provide that link and make decisions whether to manually alter his or her design. Lastly, the performance of sensitivity analyses using @RISK for Excel gives insight only into the significance of the uncertain or variable inputs into the mathematical models for generating performance estimates. However, means for circumventing this shortcoming have been proposed.

Near term improvements to the method proposed in this thesis may be accomplished by successfully addressing the above shortcomings.

CHAPTER 9

CLOSURE

Product tolerances strongly impact cost and environmental performances in manufacturing through the selection of manufacturing machinery and also the operation of that machinery; the weakness in this method is related to both. The automation of process planning at its two levels, to both generate a potential process (i.e., select the necessary processes and machinery) and set the operation parameters, is currently very difficult. Process planning is challenging and complex and it would be naïve to think that it may be simply or cursorily done, especially given the availability issues of machine level process capability information for those outside a manufacturing facility. Without this automated link in the method developed here, a user in product design must manually create potential processes and tweak the operating parameters for given part designs. For a user whose company relies on "best practices" or standards in the layout of their manufacturing processes this process becomes somewhat easier as the possible combinations of operations and machinery are greatly reduced. However, the additional process planning work and knowledge required by a product designer is not ideal as a key goal for the model is that it be easy and efficient to use so as to improve the likelihood of its implementation and provide real value in DfE efforts. Despite this operational shortcoming, the results from this method can be valuable in supporting cost and environmentally conscious DfM decision making efforts by providing product designers quantitative cost and environmental information on the manufacturing processes required to achieve their product designs.

Given the motivation to better understand the relationship between product tolerances and costs and environmental impacts in manufacturing, a method for estimating cost and environmental performances of manufacturing processes has been developed and presented. The intended use of this method is to provide these estimates as feedback information to product designers, and thus support cost and environmentally conscious design for manufacturing. Better connecting product design decisions, such as tolerances, to effects in manufacturing is helpful towards attempting to improve cost and environmental performances in manufacturing through product design.

The inclusion of uncertainty of input parameters into the method gives product designers better insight into the uncertainty of performance estimates generated with the method, and thus risks associated with decision making supported by these estimates. Auxiliary machinery is included in the method because their impacts on cost and environmental performance of a manufacturing process can be quite significant; their inclusion is recommended for most accurately estimating the full effects of a part's manufacture.

Despite the operational shortcoming related to the lack of fully automated process planning in the method, quantitative cost and environmental information of manufacturing processes estimated by this method is valuable and necessary decision support for cost and environmentally conscious manufacturing decision making efforts of product designers, and process planners, in the successful, environmentally conscious companies of tomorrow.

9.1 A Final Look at the Thesis Roadmap

After the introduction in Chapter 1 where an overview of the problem to be addressed was given, a literature review was conducted in Chapter 2 to establish the motivation for this work and identify the potential contributions to be made. The method structure and detailed workings were laid out in Chapter 3, and with Chapter 4 where the important role of databases is explained, Empirical Structural Validity was established. In Chapter 5, the instantiation of the method as a VBA-powered automated tool in Excel, coupled with @RISK software to perform uncertainty analyses was described. The Excel-based tool was exercised by two illustrative examples of increasing complexity in Chapter 6 as proof of concept and utility of the method, and to partially prove the Empirical Performance Validity of the method. A study of automotive transmission pinion gear manufacture, where gear tolerancing decisions have significant manufacturing environmental and cost performance implications, was conducted in Chapter 7 to give further evidence of Empirical Performance Validity. The thesis closed with a Critical Evaluation, of the work in Chapter 8, including a discussion of Theoretical Performance Validity, and the Closure is found here with final remarks in Chapter 9.

9.2 Contributions

The identified contributions made by this work are the following:

- A method for estimating environmental and cost performances of processes required for the manufacture of product designs has been developed. The unique and novel aspect of this method is the addition of the environmental dimension to the work of others in the area of manufacturing cost estimation. The developed method may be used in the investigation of environmental performance –

tolerance curves, the generation of empirical environment performance – tolerance models (i.e., EB = f(tolerance)), and the optimization of part feature tolerance designs with respect to manufacturing environmental and cost performances.

- Simple mathematical models for estimating environmental burdens of primary and auxiliary production machinery have been proposed. These models include the role of auxiliary machinery, in addition to primary machinery, in the performance estimates of manufacturing production lines.
- Accounting rules for situations where primary and auxiliary production machinery is shared have been proposed. Additionally, a method for the attribution of manufacturing performances per unit of production for auxiliary machinery, based on the hourly production rates of primary machinery supported, was presented.
- A case for the creation and maintenance of machine databases with cost and environmental performance information was made; in the thesis a potential beneficial use of the information contained therein was demonstrated. Alternatively, the value of creating and maintaining databases of machine operating information through their use in predictive performance estimating was established.

9.3 Future Work

The completion of this thesis is but a beginning of potential future work for further development, but mostly application, of the method. The items discussed in Chapter 8, and additional work needed, of course need to be addressed to improve the operation of the method in computer implementation, but using the method in product design where attempts to improve manufacturing cost and environmental performances are made through upfront product design is necessary to attempt to further establish the Theoretical Performance Validity of the method. The method and Excel-based tool should be applied to real manufacturing processes and part designs, and in doing so investigate the shape of environmental performance – tolerance curves. Determining if the environmental performance of part manufacture follows the cost – tolerance curve, or if they follow some other trends or behaviors would be useful and valuable information to product and process designers wishing to also improve environmental performances of part manufacture. The developed method may possibly be extended to non-machining, metal material removing manufacturing processes by examining other manufacturing processes such as injection molding, casting, forging, silicon wafer fabrication, textiles weaving, and rapid prototyping, among many others. Estimating in a predictive fashion, or merely accounting, performances of part manufacture made by other processes would also be valuable support for cost and environmentally conscious decision making activities in the manufacturing phase of a product's life cycle. Furthermore, this type of method may be applied to other generic, steady state process flows which consume resources and energy, have by-products to the environment, and cost money to achieve a desired end product, good, or service. A few examples of types of process flows to apply this or a similar method to are logistics and transportation systems, assembly of mechanical components into higher levels assemblies and systems, chemical processing, cooking or food production, and agriculture. Predicting the performance of a process flow may enable changes to be made to that process and realize cost and environmental savings that may be potentially huge, depending on the economies of scale involved.

The notion of a 'triple bottom line' was introduced back in Chapter 2, and is the idea that a company's health, well-being, and performance should be more fully measured by examining its bottom line in financial, environment, and social areas. The method proposed here has clearly examined the financial and environmental components of the triple bottom line, but neglected the social impacts as an indicator of manufacturing performance. Considering and measuring the social impacts for a full triple bottom line assessment is admittedly quite difficult given the fuzziness and scale involved in attempting to quantify one of Earth's most curious creatures: humans. Elements of social performance related to product and process design, and the ensuing manufacturing, which could be pursued and studied are (1) the effects outsourcing and offshoring manufacturing jobs and materials sourcing, (2) the health and safety implications for company workers, (3) the improved perception of a company and its reputation given commitments and efforts towards environmental initiatives, and (4) the reduction of environmental burdens and the likely positive effects on the collective health of human society, in addition to natural flora and fauna. These items under the heading of the social bottom line are quite expansive and require multi-disciplinary knowledge and expertise to even begin to quantify.

9.4 Final Remarks

Environmental sustainability is becoming increasingly important to most major corporations in the US and the rest of the world. Towards achieving environmental sustainability these companies seek to improve the environmental performances of their enterprises by reducing their respective ecological footprints. These improvements are incremental and must occur in all facets of the enterprise's operations since none are free from impacting the environment; from facilities operation and maintenance, to logistics, sales, administration, and manufacturing. The translation of high level corporate vision statements and business principles into daily operations and practices of employees throughout the company is far from trivial; especially when it comes to environmental initiatives. Environmental initiatives are generally greeted with some disdain due to the vagueness of goals, contentiousness in measuring environmental performance, and society's disinterest in and / or ignorance of environmental concerns.

However, increasing human populations, rising standards of living in newly developed nations, and the finite resources present on the Earth make pursuing better environmental performances imperative. Additionally, from a more near term business angle, the globalization of markets requires domestic companies to comply with the laws and regulations of international markets. In Europe and some parts of Asia environmental regulations are more aggressive than domestically, and thus to compete in those areas US companies are forced to toughen their own environmental policies and improve performances. While striving for environmental performance improvements in all facets of operations, numerous other demands and wishes must be satisfied by the enterprise; these objectives include making profits, reducing times to market, increasing market shares, experiencing growth, expanding to new markets, introducing innovative products, expanding product portfolios, maximizing quality, and generally running their business well and increasing shareholder value. Environmental care is another goal to be added to an already substantial list of enterprise objectives; the weighting that such a goal is given relative to other objectives is dependent on the strength of corporate, governmental, and societal commitment to environmental sustainability. The method proposed and demonstrated in this thesis, by bringing high-level environmental sustainability goals down into actual product and process design challenges, is placing just one small piece of a huge and complex puzzle that must be solved by the companies of today, and tomorrow, to achieve success in both their businesses and also for the environment.

APPENDIX A

DEVELOPED EXCEL-BASED TOOL

The contents of this Appendix serve to present the developed Excel-based tool for predicting manufacturing cost and environmental performances and is excerpted from (Bradley 2006).

1. Front End: Process Generation

The front end of the tool is where the manufacturing process to achieve the inputted part design is generated. The section contains all the relevant instructions and information for using the front end of the Predictor tool.

1.1. Step by Step guide for Front End

In this section the instructions for using the front end of the tool are given sheet by sheet. The input to the front end is the part design, and the output is a potential process to achieve that part design.

NOTE: Numbers in parentheses (#) on buttons in the sheets in the front end indicate the proper order in which macros should be activated.

1.1.1. Process Generation Sheet

In this sheet a product designer:

1. Inputs his or her part design;
2. Filters the available machines in the Primary Machine Database based on the part design;

3. Selects the desired primary machinery;
4. Returns the required auxiliary equipment, given the chosen primary machinery;
5. Selects the desired auxiliary equipment;
6. Export selected machinery (or Run All for automated processing, more on this in a later section).

A screen shot of the Process Generation Sheet's primary machine selection is given in Figure 128. The letters A, B, and C are for location reference in the instructions that follow for using this section of the tool.

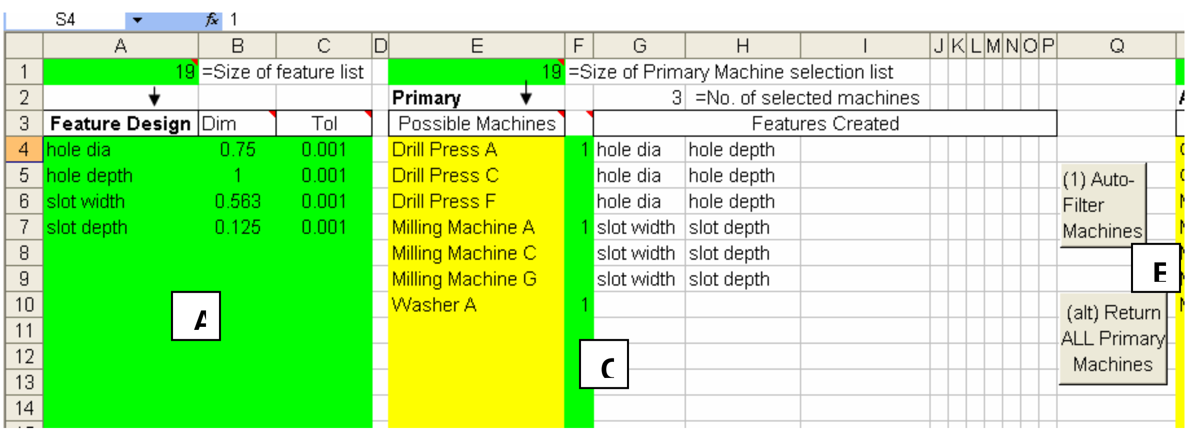


Figure 128 Screen Shot of Process Generation Sheet, Primary Machine selection

Inputting a part design (A)

In the section with the letter 'A' in Figure 128 a product designer enters his or her part design. The part design is comprised of the various critical feature attributes to be created by the manufacturing process. For each feature, the nominal dimension and tolerance on that dimension are to be specified in the correct column, in the same row as the part feature.

The units for the dimensions and tolerances may be whatever you like, but must be consistent with the units in the Primary Machine Database. Please edit the comment for the dimension and tolerance headings to include the chosen unit of measure.

For multi-dimensioned features, a separate line is used for each aspect of the feature. For example, for a blind rectangular hole feature, you would need to enter something like 'hole opening width', 'hole opening length', and 'hole depth', with the respective dimensions and tolerances.

The primary machines in the databases will be filtered based on their capabilities to create the features with the dimensions and tolerances entered here.

Before moving on from this section please be sure that the number in A1, the size of the feature list, though need not be exact, must be at least the number of features in the list below.

Return primary machines (B)

After entering all the features with their dimensions and tolerances, there are 3 methods for determining the primary machines for the potential manufacturing process.

1. *Filtering (Feature based process planning)*

Pressing the button labeled "(1) Auto-Filter Machines" will activate the macro that will filter the machines in the primary database for their capability to meet the dimensional and tolerance requirements for the part features. The macro returns these 'passing' machines in the list in column E, in the same order that they appear in the primary machine database. Running this macro will overwrite any machines that may be in column E.

For machines capable of creating multiple features, the selection of the machine is an AND operation, as opposed to an OR operation. To 'pass' and be returned they must be able to successfully create *all* the features.

To the right of the 'passing' machine list, the features that each machine creates are listed on the same row, in columns G up to P. These created features are returned to aid in machine selection, so that machines aren't selected that would duplicate features.

Primary machines that do not create features' dimensions and / or tolerances, but play critical roles in the manufacturing process, such as cleaning machines and heat treatment furnaces, need to be manually inputted as they are not automatically returned by this macro.

For machines that are manually inputted in the list in column E, they MUST be in same order as listed in primary machine database, and have EXACTLY the same name/spelling.

2. *Variant process planning*

An alternative to the feature based process planning method just presented above is to use variant process planning. This method may be used when either specific feature information (i.e., dimensions and tolerances) is not known for the part design or the machinery in the database, and / or the manufacturing process for a given part is defined by a common or best practice.

Pressing the button labeled "(alt) Return ALL Primary Machines" will activate the macro that returns a listing of all primary machines located in the database. Running this macro will overwrite any machines that may be in column E. From this complete list of primary machines the user picks the desired machines.

To the right of the machine list, the features that each machine creates are listed on the same row, in columns G up to P. These created features are returned to aid in machine selection, so that machines aren't selected that would duplicate features. NOTE: Using this method will ignore any feature design information that may have been inputted. Machine selection is solely up to the decision of the user.

3. *Manual Input*

An alternative and / or supplement to the previous two approaches is to simply type in the machines you wish to have in your process. For machines that are manually inputted in the list in column E, they MUST be in same order as listed in primary machine database, and have EXACTLY the same name/spelling.

Using the button labeled "(alt) Return ALL Primary Machines" is preferred over manually inputting *all* machines as it makes it easy to simply select the machines you want from the list of all machines, opposed to manually inputting them and making an error in either name, spelling, or order. Manual inputting is best employed in supplementing the feature based method with primary machines that do not directly create features but are vital to the manufacturing process.

NOTE: Using this method will ignore any feature design information that may have been inputted. Machine selection is solely up to the decision of the user.

Select primary machines (C)

For all 3 methods after the list in column E has been populated, the specific machines must be selected. Selection is done by placing a '1' in column F next to machines to be used. You must select at least one machine.

Only select one of each kind of machine. Number of machines may be updated in sheet "Primary Process Calc" in back end. Machines must be in same order as listed in database.

Before moving on from this section please be sure that the number in E1, the size of the Primary Machine selection list, though need not be exact, must be at least the number of machines in the list below.

A screen shot of the Process Generation Sheet's auxiliary machine selection is given in Figure 129. The letters D, E, and F are for location reference in the instructions that follow for using this section of the tool.

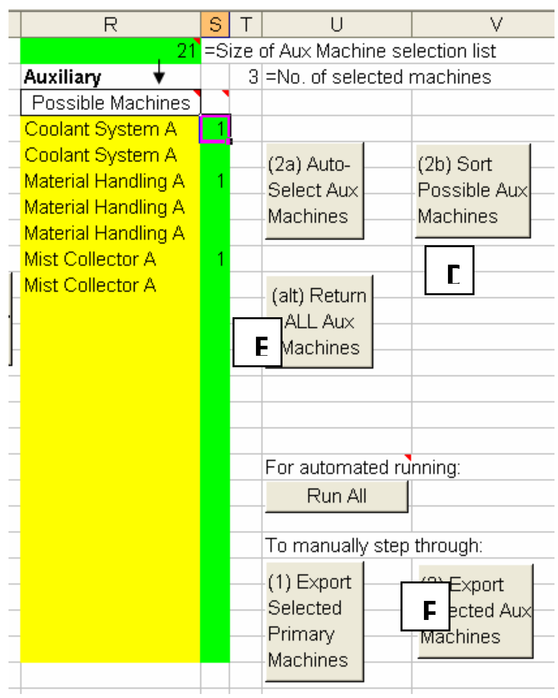


Figure 129 Screen Shot of Process Generation Sheet, Auxiliary Machinery selection

Return auxiliary machines (D)

After selecting the primary machines to be used in the manufacturing process, there are 3 methods for selecting the auxiliary machines to support those machines in the process.

1. *Auto Selection*

Pressing the button labeled "(2a) Auto-Select Aux Machines" will activate the macro that will return those auxiliary machines listed in the primary database as required for the selected primary machines chosen in column F. For example, for many dry cutting operations in a high volume manufacturing environment, a dust collector will be required as an auxiliary machine to support the primary operation of dry cutting.

The default for this macro is to assume that all auxiliary machines returned will be required in the manufacturing process. Thus, auxiliary machines are returned with a '1' already placed in the selection column S. Machines that are not desired must have their '1' deleted.

Machines that are not automatically returned may also be manually inputted if needed. For machines that are manually inputted in the list in column R, they MUST be in same order as listed in auxiliary machine database, and have EXACTLY the same name/spelling.

Before moving on, the auxiliary machines in column R must be in the same order as listed in the auxiliary machine database, which is alphabetical. To easily accomplish this press the button labeled "(2b) Sort Possible Aux Machines" will activates a macro that sorts column R and puts it in alphabetical order. Essentially this macro automates the Excel sort function.

2. *Variant process planning*

An alternative to the auto-selection method just presented above is to use variant process planning. This method may be used when the required auxiliary machines for primary machines are not known, and / or the manufacturing process for a given part is defined by a common or best practice.

Pressing the button labeled "(alt) Return ALL Aux Machines" will activate the macro that returns a listing of all auxiliary machines located in the database. Running this macro will overwrite any machines that may be in column R. From this complete list of auxiliary machines the user picks the desired machines.

NOTE: Using this method will ignore the auxiliary machine requirements in the primary machine database for those machines selected for the primary process. Machine selection is solely up to the decision of the user.

3. *Manual Input*

An alternative and / or supplement to the previous two approaches is to simply type in the machines you wish to have in your process. For machines that are manually inputted in the list in column R, they MUST be in same order as listed in auxiliary machine database, and have EXACTLY the same name/spelling.

Using the button labeled "(alt) Return ALL Aux Machines" is preferred over manually inputting *all* machines as it makes it easy to simply select the machines you want from the list of all machines, opposed to manually inputting them and making an error in either name, spelling, or order. Manual inputting is best employed in supplementing the auto-selection method.

NOTE: Using this method will ignore the auxiliary machine requirements in the primary machine database for those machines selected for the primary process. Machine selection is solely up to the decision of the user.

<u>Select auxiliary machines (E)</u>

There may only be one of each type of auxiliary machine selected, regardless of how many are returned by the auto-select method. The number of machines in the actual auxiliary process may be updated in sheet “Aux Process Calc” in the back end of the tool. For example, suppose 3 machines selected for the primary process require the same coolant system to support their operation. That coolant system would only be selected once in column S. An example of this occurring is shown in Figure 129; though multiple machines of the primary process require the same coolant system, material handling, and mist collector, only one of each type is selected. Additionally, machines must be in same order as listed in database.

FAILURE TO DO THIS WILL CAUSE ERRORS!

Before moving on from this section please be sure that the number in R1, the size of the Auxiliary Machine selection list, though need not be exact, must be at least the number of machines in the list below.

<u>Export selected machines (F)</u>

With the primary and auxiliary machines selected you’re ready to exercise the rest of tool and develop the estimates on those machines’ performance. To better understand the workings of this tool we will now manually step through the entire process. This may be automated, but please see the section on Automated Running for more information.

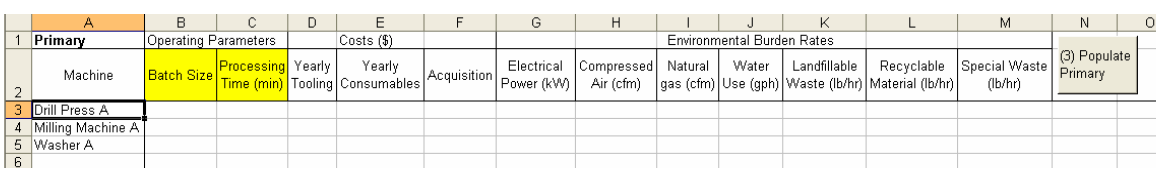
Selecting the buttons “(1) Export Selected Primary Machines” and then “(2) Export Selected Aux Machines” will activate the macros that export the selected machines to the sheets Selected Primary Machines and Selected Aux Machines, respectively. Any machines and machine information in those sheets will be cleared on running the exporting macros. After running the second export macro for the auxiliary machines you will be taken to the Selected Primary Machines sheet.

1.1.2. Selected Primary Machines Sheet

In this sheet the user:

1. Pulls machine information from the primary machine database and populate this sheet for the selected primary machines.
2. Has the opportunity to update the operating parameters batch size and processing time from the typical values contained in the database if necessary and able.

In Figures 130 and 131 below, screen shots of the Selected Primary Machines sheet are presented before and after populating from the Primary Database, respectively.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Primary	Operating Parameters			Costs ($)				Environmental Burden Rates					(3) Populate Primary	
2	Machine	Batch Size	Processing Time (min)	Yearly Tooling	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)		
3	Drill Press A														
4	Milling Machine A														
5	Washer A														
6															

Figure 130 Screen Shot of Selected Primary Machines Sheet

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	**Primary**	Operating Parameters			Costs ($)				Environmental Burden Rates					(3) Populate Primary	
2	Machine	Batch Size	Processing Time (min)	Yearly Tooling	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)		
3	Drill Press A	1	0.5	15000	10250	100000	10	5	0	0	2	13	5		
4	Milling Machine A	1	0.75	50000	25000	250000	5	10	0	0	3	3.75	2		
5	Washer A	15	5	5000	15000	500000	15	100	0	8	5	0.5	2		

Figure 131 Screen Shot of Selected Primary Machines Sheet, after populating

Columns B and C may be manually updated from the typical values contained in the database to more accurately reflect the actual process. Input from process planners and manufacturing engineers is necessary here to update the operating parameters as a function of the part feature tolerances to be achieved. Unless the product designer is knowledgeable in this relationship, this updating should be the responsibility of process planners / engineers.

A macro has been written that finds the selected machines in column A in the Primary Database and pulls the required information from that database and into this sheet. This macro may be activated simply by pressing the “(3) Populate Primary” button.

WARNING: Running this macro will overwrite any information manually inputted to update the machine operating parameters.

After populating the Selected Primary Machines sheet with the macro you will be taken to the Selected Aux Machine sheet.

1.1.3. Selected Aux Machines Sheet

In this sheet the user:

1. Pulls machine information from the auxiliary machine database and populate this sheet for the selected auxiliary machines.

In Figures 132 and 133 below, screen shots of the Selected Aux Machines sheet are presented before and after populating from the Auxiliary Database, respectively.

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Auxiliary**	Costs ($)		Environmental Burden Rates							(4) Populate Auxiliary	Continue to workbook:
2	Machine	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)		back_end_[date]
3	Coolant System A											
4	Material Handling A											
5	Mist Collector A											

Figure 132 Screen Shot of Selected Aux Machines Sheet

A3 Coolant System A

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Auxiliary**	Costs ($)		Environmental Burden Rates							(4) Populate Auxiliary	Continue to workbook:
2	Machine	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)		back_end_[date]
3	Coolant System A	20000	250000	3.5	10	0	11.5	10	0	9		
4	Material Handling A	2300	50000	5.5	3.5	0	0.7	0.625	0	0.625		
5	Mist Collector A	11750	95000	10	5	0	0	2.5	0	4		
6												

Figure 133 Screen Shot of Selected Aux Machines Sheet, after populating

A macro has been written that finds the selected machines in column A in the Auxiliary Database and pulls the required information from that database and into this sheet. This macro may be activated simply by pressing the “(4) Populate Auxiliary” button.

After populating the Selected Aux Machines sheet with the macro, you should continue to the back end file of the tool, specifically to the workbook “Proposed Primary Process”.

1.1.4. Primary DB Sheet

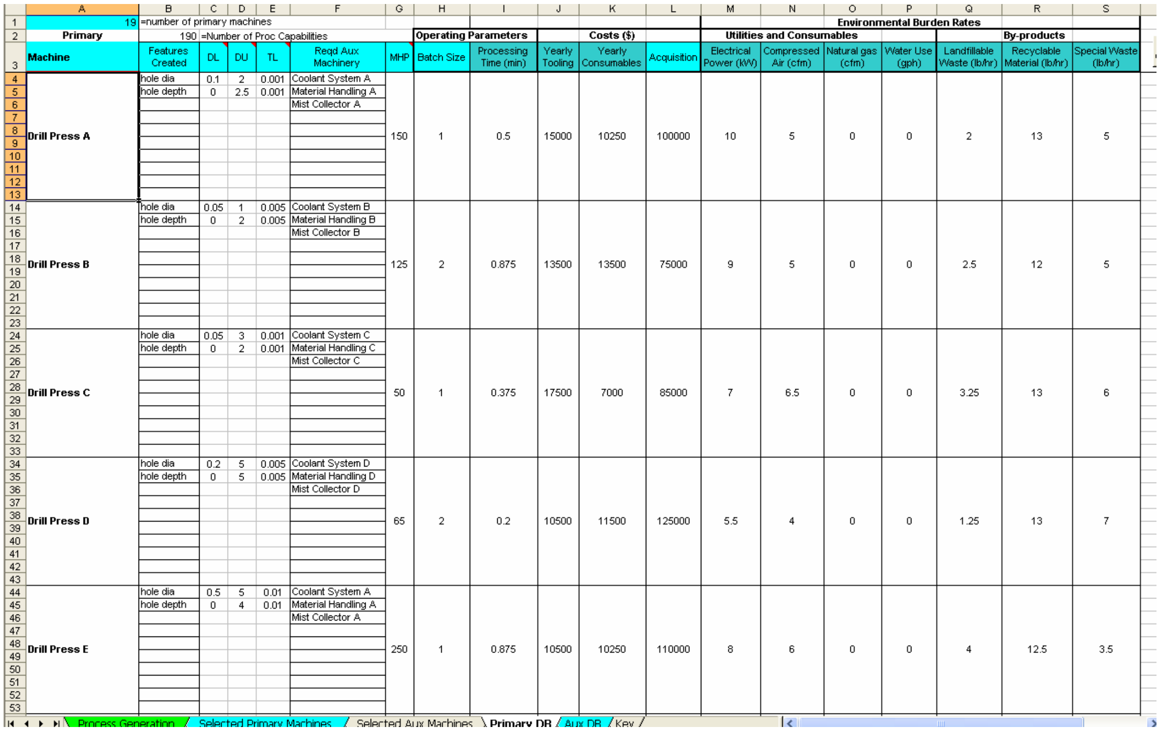
In this sheet:

1. Exist the entries for primary machines that are capable of producing the features for a particular type of part.

It should be the responsibility of manufacturing engineers and process planners to populate and maintain this database. A screen shot of the implemented primary database is shown in Figure 134.

For each machine entry there is:

- Producibility data related to
    a. features created by the machine (≤ 10)
    b. dimensional capability (lower and upper bounds) for each feature
    c. tolerance capability (lower bound) for each feature
    d. maximum hourly production rate
- Required auxiliary machinery to support the primary machine operation (≤ 10)
- Typical operating parameters
    a. batch size
    b. processing time
- Costs
    a. yearly tooling
    b. yearly consumables (e.g., filters, fluids, etc.)
    c. initial acquisition cost
- Environmental Burden Rates
    a. Utilities and consumables (e.g., electricity, compressed air, natural gas, water, etc.)
    b. by-products (e.g., landfillable waste, recyclable materials, special wastes, etc.)



19 =number of primary machines

190 =Number of Proc Capabilities

Primary Machine	Features Created	DL	DU	TL	Reqd Aux Machinery	MHP	Operating Parameters: Batch Size	Processing Time (min)	Yearly Tooling	Costs ($): Yearly Consumables	Acquisition	Environmental Burden Rates — Utilities and Consumables: Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	By-products: Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)
Drill Press A	hole dia hole depth	0.1 0	2 2.5	0.001 0.001	Coolant System A Material Handling A Mist Collector A	150	1	0.5	15000	10250	100000	10	5	0	0	2	13	5
Drill Press B	hole dia hole depth	0.05 0	1 2	0.005 0.005	Coolant System B Material Handling B Mist Collector B	125	2	0.875	13500	13500	75000	9	5	0	0	2.5	12	5
Drill Press C	hole dia hole depth	0.05 0	3 2	0.001 0.001	Coolant System C Material Handling C Mist Collector C	50	1	0.375	17500	7000	85000	7	6.5	0	0	3.25	13	6
Drill Press D	hole dia hole depth	0.2 0	5 5	0.005 0.005	Coolant System D Material Handling D Mist Collector D	65	2	0.2	10500	11500	125000	5.5	4	0	0	1.25	13	7
Drill Press E	hole dia hole depth	0.5 0	5 4	0.01 0.01	Coolant System A Material Handling A Mist Collector A	250	1	0.875	10500	10250	110000	8	6	0	0	4	12.5	3.5

Process Generation / Selected Primary Machines / Selected Aux Machines / Primary DB / Aux DB / Key

Figure 134 Screen Shot of Primary DB Sheet

Machine entries must be in alphabetical order, except for those machines without features it creates. Those machines, such as washers and heat treatment furnaces, should be placed after the machines that directly create features, and then in alphabetical order.

VERY IMPORTANT: Please be sure that the number of primary machines in the database, located at A1, is correct!

The format of a machine entry row is as follows:

- Height is 10 rows in Excel to accommodate up to 10 ‘features created’ and ‘required auxiliary machinery’ for each primary machine.
- Except for columns B, C, D, E, and F, each column has 10 rows merged to create one cell with height of 10 rows.

- For merged cells, it is recommended that the vertical alignment be set to center for ease of viewing.

Incorporating Uncertainty

The value of many items in the primary machine database will not be known with perfect certainty. The use of @RISK functions is prescribed to capture the uncertainty information for primary machine entries. The color of headings for columns denotes which items typically will have uncertainty and variability, per the key.

For entries with very little information the use of uniform probability density functions is recommended. A lower and upper bound is specified and all points within the range are equally probable to occur. By the Central Limit Theorem, results will tend to the outcome of using the mean, expected value of all inputs. The results' minima and maxima are found using the respective extrema of the inputs to mathematical models.

For entries with more information known, perhaps from empirical results and experimentation, other probability density functions may be ascribed which model the entry's behavior. Typically, a distribution will be assumed to be normal with a mean (μ) and standard deviation (σ), but any other common distribution that is empirically determined may be employed.

When information is wholly unknown the cell should be left empty to indicate this ignorance. If possible, effort should be made to address these gaps in the database.

WARNING: Leaving a cell blank will cause the result of computations to be ZERO. Please consider this when interpreting results; a result of ZERO does not necessarily indicate a zero value but rather that machine information may be missing.

The Use of Pull Down Lists for ‘Features Created’ and ‘Required Auxiliary Machinery’

The part features, as entered on the Process Generation sheet, will appear to the far right in column BD, and the available auxiliary machines, as entered in the Auxiliary DB, will appear in column BE. The listing of the part features and auxiliary machines here allows for the use of ‘pull down lists’ when populating the entries for primary machines.

For a given primary machine, to add the features created by that machine, select a row in the ‘Features Created’ column, and then select the feature from the pull down list. Only features from that list may be inputted.

The same procedure is used to add required auxiliary machines for a primary machine. Using these pull down lists ensures that the exact same feature and auxiliary machine names/spellings are used throughout.

1.1.5. Auxiliary DB Sheet

In this sheet:

1. There exist entries for auxiliary machines that support primary machine operation.

It should be the responsibility of manufacturing engineers and process planners to populate and maintain this database. A screen shot of the implemented auxiliary database is given in Figure 135.

For each machine entry there are:

- Costs
    a. yearly consumables (e.g., filters, fluids, etc.)

b. initial acquisition cost

- Environmental Burden Rates

    a. utilities and consumables (e.g., electricity, compressed air, natural gas, water, etc.)

    b. by-products (e.g., landfillable waste, recyclable materials, special wastes, etc.)

	A	B	C	D	E	F	G	H	I	J
1	12	=number of auxiliary machines								
2						Environmental Burden Rates				
3	Auxiliary	Costs		Utilities and Consumables				By-products		
4	Machine	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)
5	Coolant System A	20000	250000	3.5	10	0	11.5	10	0	9
6	Coolant System B	15000	300000	5	7	0	10	8.5	0	10
7	Coolant System C	20000	275000	2	5	0	7.5	9.5	0	7
8	Coolant System D	21000	200000	5.5	6	0	13	7.5	0	8
9	Material Handling A	2300	50000	5.5	3.5	0	0.7	0.625	0	0.625
10	Material Handling B	4500	75000	7	3	0	0.5	0.5	0	0.5
11	Material Handling C	2250	45000	4.5	2.5	0	0.6	0.75	0	0.3
12	Material Handling D	2850	80000	8	5	0	0.7	0.875	0	0.75
13	Mist Collector A	11750	95000	10	5	0	0	2.5	0	4
14	Mist Collector B	13000	100000	9	6	0	0	3.5	0	3.5
15	Mist Collector C	8000	85000	11	4.5	0	0	3.5	0	4.5
16	Mist Collector D	8750	90000	7	7	0	0	2.75	0	3
17										

Figure 135 Screenshot of Aux DB Sheet

Machine entries must be in alphabetical order. There is no special formatting for the auxiliary machine entry rows; each row has a height of 1 row.

VERY IMPORTANT: Please be sure that the number of auxiliary machines in the database, located at A1, is correct!

Incorporating Uncertainty

The value of many items in the auxiliary machine database will not be known with perfect certainty. The use of @RISK functions is prescribed to capture the uncertainty information for auxiliary machine entries. The color of headings for columns denotes which items typically will have uncertainty and variability, per the key.

When information is wholly unknown the cell should be left empty to indicate this ignorance. If possible, effort should be made to address these gaps in the database.

WARNING: Leaving a cell blank will cause the result of computations to be ZERO. Please consider this when interpreting results; a result of ZERO does not necessarily indicate a zero value but rather that machine information may be missing.

2. Back End: Process Accounting

The back end of the tool is where the cost and environmental performance of the manufacturing process proposed / selected in the front end of the tool is calculated. The section contains all the relevant instructions and information for using the back end of the Predictor tool.

2.1. Step by Step guide for Back End

In this section the instructions for using the back end of the tool are given sheet by sheet. The input to the back end is the proposed manufacturing process, and the outputs are the cost and environmental performance of that process measured in terms of an environmental inventory (burdens), an environmental impact score, and financial cost.

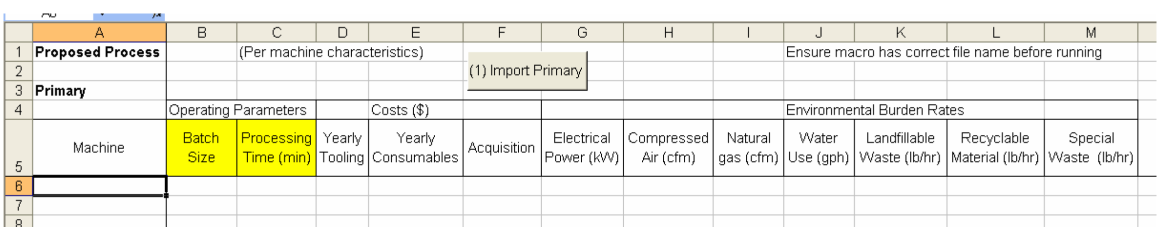
NOTE: Numbers in parentheses (#) on buttons in the sheets in the front end indicate the proper order in which macros should be activated.

2.1.1. Proposed Primary Process Sheet

In this sheet the user:

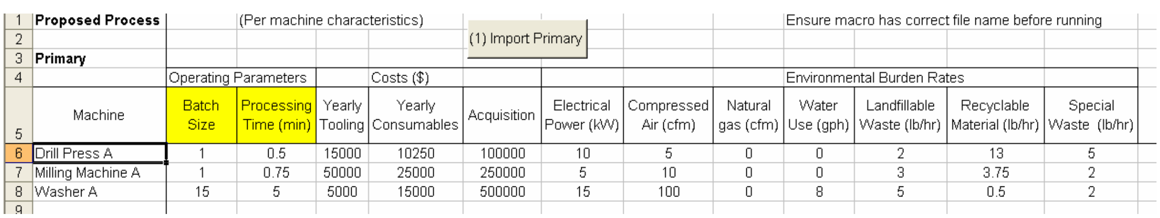
1. Imports the selected primary machines and machine information from the Selected Primary Machines sheet in the front end.
2. Has the opportunity to update the operating parameters batch size and processing time from the typical values contained in the database if necessary and able.

In Figures 136 and 137 below, screen shots of the Proposed Primary Process sheet are presented before and after importing from the Selected Primary Machines sheet in the front end, respectively.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Proposed Process**		(Per machine characteristics)							Ensure macro has correct file name before running			
2						(1) Import Primary							
3	**Primary**												
4		Operating Parameters			Costs ($)					Environmental Burden Rates			
5	Machine	Batch Size	Processing Time (min)	Yearly Tooling	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)
6													
7													
8													

Figure 136 Screen Shot of Proposed Primary Process Sheet



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Proposed Process**		(Per machine characteristics)							Ensure macro has correct file name before running			
2						(1) Import Primary							
3	**Primary**												
4		Operating Parameters			Costs ($)					Environmental Burden Rates			
5	Machine	Batch Size	Processing Time (min)	Yearly Tooling	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)
6	Drill Press A	1	0.5	15000	10250	100000	10	5	0	0	2	13	5
7	Milling Machine A	1	0.75	50000	25000	250000	5	10	0	0	3	3.75	2
8	Washer A	15	5	5000	15000	500000	15	100	0	8	5	0.5	2
9													

Figure 137 Screen Shot of Proposed Primary Process Sheet, after importing from Front End

Columns B and C may be manually updated from the typical values contained in the database to more accurately reflect the actual process, if not already done so in the front end. Input from process planners and manufacturing engineers is necessary here to update the operating parameters as a function of the part feature tolerances to be achieved. Unless the product designer is knowledgeable in this relationship, this updating should be the responsibility of process planners / engineers.

A macro has been written that copies the machines and machine information from the front end to this sheet. This macro may be activated simply by pressing the “(1) Import Primary” button.

WARNING: Running this macro will overwrite any information previously manually inputted to update the machine operating parameters.

After importing the Proposed Primary Process with the macro you should proceed to the Proposed Aux Process sheet to do the same tasks there.

2.1.2. Proposed Aux Process Sheet

In this sheet the user:

1. Imports the selected auxiliary machines and machine information from the Selected Aux Machines sheet in the front end.

In Figures 138 and 139 below, screen shots of the Proposed Aux Process sheet are presented before and after importing from the Selected Aux Machines sheet in the front end, respectively.

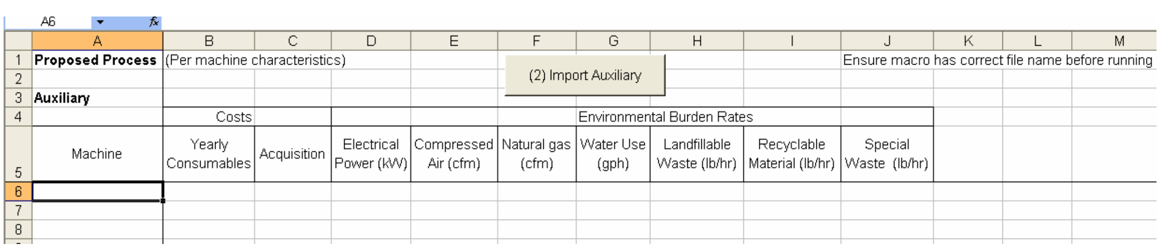
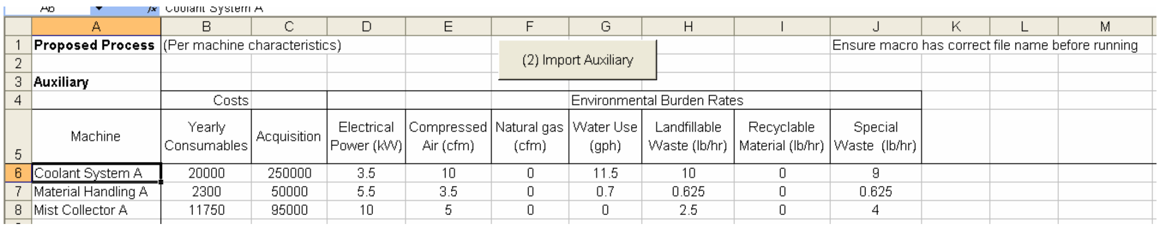


Figure 138 Screen Shot of Proposed Aux Process Sheet



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Proposed Process**	(Per machine characteristics)				(2) Import Auxiliary				Ensure macro has correct file name before running			
2													
3	**Auxiliary**												
4		Costs		Environmental Burden Rates									
5	Machine	Yearly Consumables	Acquisition	Electrical Power (kW)	Compressed Air (cfm)	Natural gas (cfm)	Water Use (gph)	Landfillable Waste (lb/hr)	Recyclable Material (lb/hr)	Special Waste (lb/hr)			
6	Coolant System A	20000	250000	3.5	10	0	11.5	10	0	9			
7	Material Handling A	2300	50000	5.5	3.5	0	0.7	0.625	0	0.625			
8	Mist Collector A	11750	95000	10	5	0	0	2.5	0	4			

Figure 139 Screen Shot of Proposed Aux Process Sheet, after importing from Front End

A macro has been written that copies the machines and machine information from the front end to this sheet. This macro may be activated simply by pressing the "(2) Import Auxiliary" button.

After importing the Proposed Aux Process with the macro you should proceed to the Primary Process Calc sheet.

2.1.3. Primary Process Calc Sheet

In this sheet the user:

1. Applies the mathematical models to each primary machine to generate the inventory of environmental burdens and 'traditional' machine costs, as well as determining the environmental impacts and total financial costs from that inventory, all on a per unit of production basis.
2. May update the number of each primary machine to reflect the number of machines required in the manufacturing process.
3. Aggregates the inventory, environmental impacts, and financial costs for all primary machines in the proposed process.

In Figures 140 and 141 below, screen shots of the Primary Process Calc sheet are presented before and after 'filling and calculating', respectively.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Proposed Process Characteristics**												
2	(per unit of production basis)			(3) Fill and Calculate Primary			Primary Model Information		Save Primary Models				
3													
4	Can accept up to 50 machines									**INVENTORY**			
5		No. Machines	Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
6	**Total:**	3	0.229	43.333	9.100	0.000	0.000	9.329	0.044	0.082	0.158	0.078	12.464
7													
8	**Primary**						**Environmental Burdens**						
9	Machine	No. Machines	Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
10	Drill Press A	1	0.083	2.5	0.525	0.0	0.000	0.608	0.000	0.017	0.108	0.042	0.813
11													
12													

Figure 140 Screen Shot of Primary Process Calc Sheet, before filling and calculating

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Proposed Process Characteristics**												
2	(per unit of production basis)			(3) Fill and Calculate Primary			Primary Model Information		Save Primary Models				
3													
4	Can accept up to 50 machines									**INVENTORY**			
5		No. Machines	Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
6	**Total:**	3	0.229	43.333	9.100	0.000	0.000	9.329	0.044	0.082	0.158	0.078	12.464
7													
8	**Primary**						**Environmental Burdens**						
9	Machine	No. Machines	Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
10	Drill Press A	1	0.083	2.5	0.525	0.0	0.000	0.608	0.000	0.017	0.108	0.042	0.813
11	Milling Machine A	1	0.063	7.5	1.575	0.0	0.000	1.638	0.000	0.038	0.047	0.025	2.188
12	Washer A	1	0.083	33.3	7.000	0.0	0.000	7.083	0.044	0.028	0.003	0.011	9.463
13													

Figure 141 Screen Shot of Primary Process Calc Sheet, after filling and calculating

The macro activated by pressing the "(3) Fill and Calculate Primary" button fills downward so that each primary machine in the proposed process has a row entry. Models are initially stored in row 10, but are referenced appropriately so as to calculate correctly when filled down the sheet. The number of machines in the process determines how far down the sheet cells will be filled. Running this macro will overwrite any information previously inputted manually for the number of machines in column B.

The totals for each item are located in row 6 across the top. Per machine calculations for each item are found on the row for each particular machine. Please see the section on Mathematical Models for further explanation of the models used. For each of the headings in row 9 a comment is inserted explaining the exact model used to calculate that item.

The quantities calculated are per unit of production and fall under the following headings:

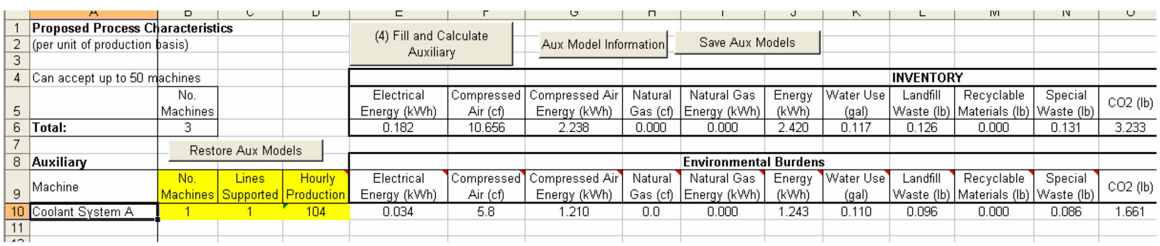
- Inventory
  - Environmental Burdens
    - utilities
    - energy
    - by-products
  - Machine ‘traditional costs’
    - tooling
    - consumables
    - acquisition
- Environmental Impacts (mpt)
  - Utilities
  - By-products
  - Total
- Financial Costs ($)
  - Utilities
  - By-products
  - Traditional
  - Total (minus direct labor)

2.1.4. Aux Process Calc Sheet

In this sheet the user:

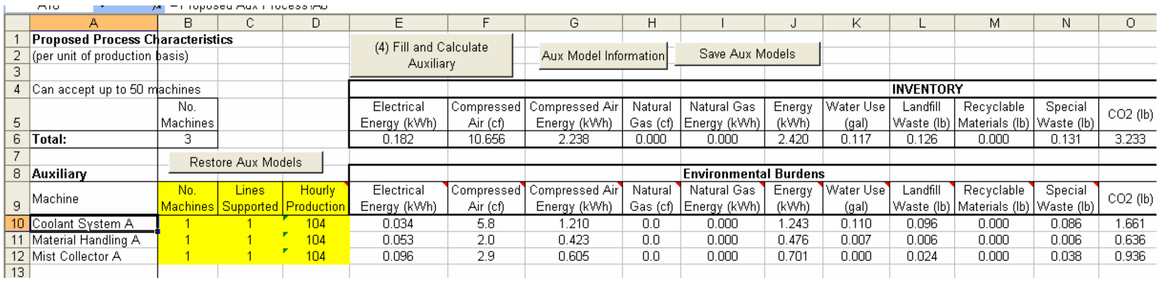
1. Applies the mathematical models to each auxiliary machine to generate the inventory of environmental burdens and 'traditional' machine costs, as well as determining the environmental impacts and total financial costs from that inventory, all on a per unit of production basis.
2. May update the number of each auxiliary machine to reflect the number of machines required in the manufacturing process, as well as the total number of production lines supported, and the hourly production rate supported.
3. Aggregates the inventory, environmental impacts, and financial costs for all auxiliary machines in the proposed process.

In Figures 142 and 143 below, screen shots of the Aux Process Calc sheet are presented before and after 'filling and calculating', respectively.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	**Proposed Process Characteristics**				(4) Fill and Calculate Auxiliary		Aux Model Information		Save Aux Models						
2	(per unit of production basis)														
3															
4	Can accept up to 50 machines											**INVENTORY**			
5		No. Machines			Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
6	**Total:**	3			0.182	10.656	2.238	0.000	0.000	2.420	0.117	0.126	0.000	0.131	3.233
7		Restore Aux Models													
8	**Auxiliary**								**Environmental Burdens**						
9	Machine	No. Machines	Lines Supported	Hourly Production	Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
10	Coolant System A	1	1	104	0.034	5.8	1.210	0.0	0.000	1.243	0.110	0.096	0.000	0.086	1.661
11															

Figure 142 Screen Shot of Primary Process Calc Sheet, before filling and calculating



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	**Proposed Process Characteristics**				(4) Fill and Calculate Auxiliary		Aux Model Information		Save Aux Models						
2	(per unit of production basis)														
3															
4	Can accept up to 50 machines											**INVENTORY**			
5		No. Machines			Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
6	**Total:**	3			0.182	10.656	2.238	0.000	0.000	2.420	0.117	0.126	0.000	0.131	3.233
7		Restore Aux Models													
8	**Auxiliary**								**Environmental Burdens**						
9	Machine	No. Machines	Lines Supported	Hourly Production	Electrical Energy (kWh)	Compressed Air (cf)	Compressed Air Energy (kWh)	Natural Gas (cf)	Natural Gas Energy (kWh)	Energy (kWh)	Water Use (gal)	Landfill Waste (lb)	Recyclable Materials (lb)	Special Waste (lb)	CO2 (lb)
10	Coolant System A	1	1	104	0.034	5.8	1.210	0.0	0.000	1.243	0.110	0.096	0.000	0.086	1.661
11	Material Handling A	1	1	104	0.053	2.0	0.423	0.0	0.000	0.476	0.007	0.006	0.000	0.006	0.636
12	Mist Collector A	1	1	104	0.096	2.9	0.605	0.0	0.000	0.701	0.000	0.024	0.000	0.038	0.936
13															

Figure 143 Screen Shot of Primary Process Calc Sheet, after filling and calculating

The macro activated by pressing the "(4) Fill and Calculate Auxiliary" button fills downward so that each auxiliary machine in the proposed process has a row entry. Models are initially stored in row 10, but are referenced appropriately so as to calculate correctly when filled down the sheet. The number of machines in the process determines how far down the sheet cells will be filled. Running this macro will overwrite any information previously inputted manually in columns B, C, and D.

The totals for each item are located in row 6 across the top. Per machine calculations for each item are found on the row for each particular machine. Please see the section on Mathematical Models for further explanation of the models used. For each of the headings in row 9 a comment is inserted explaining the exact model used to calculate that item.

The quantities calculated are per unit of production and fall under the following headings:

- Inventory
    - Environmental Burdens
        - utilities
        - energy

        - by-products
    - Machine ‘traditional costs’
        - consumables
        - acquisition
- Environmental Impacts (mpt)
    - Utilities
    - By-products
    - Total
- Financial Costs ($)
    - Utilities
    - By-products
    - Traditional
    - Total

2.1.5. Summary Outputs Sheet

In this sheet the user:

1. Finds the aggregate results for the proposed primary and auxiliary manufacturing process performance.
2. Finds the high level breakdown of environmental impacts and financial costs into main categories.
3. Finds the percentage breakdown of results by machine type; that is, by primary and auxiliary machinery.

This sheet, as the name implies, is the main source for results information, at the highest level. The sources of the information in this sheet are the individual sheets for Environmental Inventory, Environmental Impacts, and Financial Costs. Looking to those sheets will provide more disaggregated results and a greater extent of lower level details. The sources of the information in those sheets are the per machine calculations found in the Primary Process Calc and Aux Process Calc sheets and is the most disaggregated, providing the greatest extent of detail.

In Figure 144 is a screen shot of the Summary Outputs sheet for an example process.

		Primary	Auxiliary	Total	units
Main	Environmental SPS	291.101	76.863	367.965	mpt / part
	Financial Cost	3.556	0.702	4.258	$ / part
Inventory	Water Use	0.044	0.117	0.162	gal / part
	Landfill Waste	0.082	0.126	0.208	lb / part
	Recyclable Material	0.158	0.000	0.158	lb / part
	Special Waste	0.078	0.131	0.209	lb / part
	Energy	9.329	2.420	11.749	kWh / part
	CO2	12.464	3.233	15.697	lb / part

Breaking down Main Outputs by Categories:

		Primary	Auxiliary	Total	units
Env	Utilities	239.461	62.121	301.582	mpt / part
	By-products	51.640	14.742	66.383	mpt / part
Costs	Utilities	0.876	0.221	1.097	$ / part
	By-products	-0.015	0.007	-0.008	$ / part
	Other / Traditional	1.255	0.474	1.729	$ / part
	Labor	1.440	0.000	1.440	$ / part

Breaking down Outputs by Machine Type:

		Primary	Auxiliary
Main	Environmental SPS	79.1%	20.9%
	Financial Cost	83.5%	16.5%
Inventory	Water Use	27.5%	72.5%
	Landfill Waste	39.4%	60.6%
	Recyclable Material	100.0%	0.0%
	Special Waste	37.3%	62.7%
	Energy	79.4%	20.6%
	CO2	79.4%	20.6%
		Primary	**Auxiliary**
Env	Utilities	79.4%	20.6%
	By-products	77.8%	22.2%
Costs	Utilities	79.9%	20.1%
	By-products	195.7%	-95.7%
	Traditional	72.6%	27.4%
	Labor	100.0%	0.0%

Machines in Proposed Process

Primary	Auxiliary
Drill Press A	Coolant System A
Milling Machine A	Material Handling A
Washer A	Mist Collector A

Figure 144 Screen Shot of Summary Outputs Sheet

The table in the upper left hand side of Figure 144 contains the main outputs and the environmental burdens in the inventory, all in units that are per unit of production. The environmental inventory, environmental impacts, and financial costs are comprised of the following:

- Environmental Burdens: energy (e.g., electricity, compressed air, steam, and natural gas), water use, and by-products (e.g., CO2, landfillable and hazardous wastes, and recyclable materials);
- Environmental Impacts: sum of the conversion of all the environmental burdens to impacts using eco-indicator values;
- Financial Costs: tooling, consumables (e.g., filters and fluids), acquisition (i.e., initial machinery purchase), direct labor, utilities usage, and by-products disposition. Utilities usage and by-products disposition are converted from the environmental burdens in those categories via cost rates.

Environmental impacts may be converted from an inventory of environmental burdens through the use of indicators, such as Eco-indicator 99, which allows the calculation of a cumulative environmental single point score (SPS). Thus the useful outputs for a product designer, which could be factored into design decision making are the environmental burden inventory, the single point score, and the cumulative financial costs.

Results are broken down in the right hand side tables by machine type in order to show the relative contribution of the primary and auxiliary machinery to the total manufacturing performance. The contribution of auxiliary machinery to this performance is especially interesting since it is typically not considered.

The primary and auxiliary machinery in the proposed process for which the analysis has just been run are listed in the columns on the far right as reference.

If there are additions to items to be calculated as environmental burdens, the tables may need updating. Please see the section on adding and deleting environmental burden rates for more information.

2.1.6. Environmental Inventory Sheet

In this sheet the user:

1. Finds more detailed information on the environmental inventory for the proposed primary and auxiliary manufacturing process.
2. Defines @RISK outputs for inventory items of interest.

A screen shot of the Environmental Inventory sheet is shown below in Figure 145.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	**Inventory of Environmental Burdens**																
2																	
3	**Utilities and Consumables**	**Primary**	**Auxiliary**	**Total**	**Units**		**By-products**	**Primary**	**Auxiliary**	**Total**	**Units**		**Other**	**Primary**	**Auxiliary**	**Total**	**Units**
4	Electrical Energy	0.229	0.182	0.412	kWh / part		Landfill Waste	0.082	0.126	0.208	lb / part						
5	Compressed Air	43.333	10.656	53.989	cf / part		Recyclable Material	0.158	0.000	0.158	lb / part						
6	Compressed Air Energy	9.100	2.238	11.338	kWh / part		Special Waste	0.078	0.131	0.209	lb / part						
7	Natural Gas	0.000	0.000	0.000	cf / part		CO2	0.006	0.002	0.008	tons / part						
8	Natural Gas Energy	0.000	0.000	0.000	kWh / part												
9	Energy	9.329	2.420	11.749	kWh / part												
10	Water Use	0.044	0.117	0.162	gal / part												
11																	
12																	

Figure 145 Screen Shot of Environmental Inventory Sheet

The sources of the information for this sheet are the Primary Process Calc and Aux Process Calc sheets. The totals for each of the environmental inventory categories are recorded here, and are broken down into the categories of ‘utilities and consumables’, ‘by-products’, and ‘other’.

Generally it is interesting to record @RISK outputs for all items in the environmental inventory to study the uncertainty / variability of their calculated estimate. However, for energy sources whose typical units are not units of energy (e.g., compressed air in cf, natural gas in cf, steam in lb, etc.) the converted item is not as descriptive as a recorded output. It is recommended that the energy source with its typical units be recorded and not its conversion; the sum of all energy sources should be recorded though. For more information on defining @RISK Outputs please see the section on using @RISK.

If there are additions to items to be calculated as environmental burdens, the tables may need updating. Please see the section on adding and deleting environmental burden rates for more information.

2.1.7. Environmental Impacts Sheet

In this sheet the user:

1. Finds more detailed information on the environmental impacts for the proposed primary and auxiliary manufacturing process.
2. Defines @RISK outputs for impact items of interest.

A screen shot of the Environmental Inventory sheet is shown below in Figure 146.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	**Environmental Impacts**													
2	Units are mpt / part													
3														
4	Total Primary	291.102												
5	Total Auxiliary	76.864												
6	Total	367.966												
7														
8														
9	**Utilities and Consumables**	**Primary**	**Auxiliary**	**Total**		**By-products**	**Primary**	**Auxiliary**	**Total**		**Other**	**Primary**	**Auxiliary**	**Total**
10	Totals:	239.461	62.122	301.583		Totals:	51.640	14.742	66.383		Totals:	0.000	0.000	0.000
11														
12	**Utilities and Consumables**	**Primary**	**Auxiliary**	**Total**		**By-products**	**Primary**	**Auxiliary**	**Total**		**Other**	**Primary**	**Auxiliary**	**Total**
13	Electrical Energy	5.882	4.682	10.564		Landfill Waste	0.114	0.176	0.291					
14	Compressed Air	233.579	57.439	291.018		Recyclable Material	-3.433	0.000	-3.433					
15	Natural Gas	0.000	0.000	0.000		Special Waste	0.217	0.365	0.583					
16	Water	0.000	0.001	0.002		CO2	54.741	14.201	68.942					

Figure 146 Screen Shot of Environmental Impacts Sheet

The sources of the information for this sheet are the Primary Process Calc and Aux Process Calc sheets. The totals for each of the environmental impact categories are recorded here, and are broken down into the categories of ‘utilities and consumables’, ‘by-products’, and ‘other’.

The only items on this sheet that are recorded as @RISK outputs are the summed totals for the different machine types in the categories. The total environmental impact score for the primary and auxiliary processes are recorded separately, along with the total impact of the entire proposed manufacturing process.

If there are additions to items to be calculated as environmental burdens which have impacts, the tables may need updating. Please see the section on adding and deleting environmental burden rates for more information.

2.1.8. Financial Costs Sheet

In this sheet the user:

1. Finds more detailed information on the financial costs for the proposed primary and auxiliary manufacturing process.
2. Defines @RISK outputs for financial cost items of interest.

A screen shot of the Environmental Inventory sheet is shown below in Figure 147.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	**Financial Costs**													
2	Units are $ / part													
3														
4	Direct Labor	1.440												
5	Total Primary	2.116												
6	Total Auxiliary	0.702												
7	Total	4.258												
8														
9	**Utilities and Consumables**	**Primary**	**Auxiliary**	**Total**		**By-products**	**Primary**	**Auxiliary**	**Total**		**Other / Traditional**	**Primary**	**Auxiliary**	**Total**
10	Totals:	0.876	0.221	1.097		Totals:	-0.015	0.007	-0.008		Totals:	1.255	0.474	1.729
11														
12	**Utilities and Consumables**	**Primary**	**Auxiliary**	**Total**		**By-products**	**Primary**	**Auxiliary**	**Total**		**Other**	**Primary**	**Auxiliary**	**Total**
13	Electrical Energy	0.009	0.007	0.016		Landfill Waste	0.002	0.002	0.004		Per Piece Tooling	0.350	--	0.350
14	Compressed Air	0.867	0.213	1.080		Recyclable Material	-0.020	0.000	-0.020		Per Piece Consumables	0.251	0.170	0.422
15	Natural Gas	0.000	0.000	0.000		Special Waste	0.003	0.005	0.008		Per Piece Acquisition	0.654	0.304	0.958
16	Water	0.000	0.000	0.000										

Figure 147 Screen Shot of Financial Costs Sheet

The sources of the information for this sheet are the Primary Process Calc and Aux Process Calc sheets. The totals for each of the financial cost categories are recorded here, and are broken down into the categories of 'utilities and consumables', 'by-products', and 'other / traditional'.

The only items on this sheet that are recorded as @RISK outputs are the summed totals for the different machine types in the categories. The total financial costs for the primary and auxiliary processes are recorded separately, along with the total cost of the entire proposed manufacturing process.

If there are additions to items to be calculated as environmental burdens which incur cost, the tables may need updating. Please see the section on adding and deleting environmental burden rates for more information.

2.1.9. Costs & Eco-Indicators Sheet

In this sheet the user:

1. Stores the eco-indicator values and cost rates for utilities and by-products of the manufacturing process.

A screen shot of the Cost & Eco-Indicators sheet is shown below in Figure 148.

Eco-indicators								
Utilities and Consumables			By-products			Other		
Item	Value	Units	Item	Value	Units	Item	Value	Units
Electricty	25.668	mpt/kWh	Landfilling	1.397	mpt/lb			
Compressed Air	25.668	mpt/kWh	Recycling	-21.727	mpt/lb			
Natural Gas	0.101	mpt/cf	Special Wastes	2.794	mpt/lb			
Water	0.001	mpt/gal	CO2	8784.029	mpt/ton			

Costs								
Utilities and Consumables			By-products			Other		
Item	Value	Units	Item	Value	Units	Item	Value	Units
Electrical Energy	0.0400	$/kWh	Regular Landfilling	37.5000	$/ton	Operator Labor	50.0000	$/hr
Compressed Air	0.0200	$/cf	Recycling	(250.0000)	$/ton			
Natural Gas	0.0070	$/cf	Special Wastes	77.5000	$/ton			
Water	0.0024	$/gal						
Steam	0.0096							

Figure 148 Screen Shot of Cost & Eco-Indicators Sheet

As many entries as are needed may be placed into this database of costs and eco-indicators. The values placed here are used to convert items in the environmental inventory of burdens into financial costs and environmental impact scores. Cost rates may be found from internal company sources, the US Department of Energy, utilities companies, and / or service providers. Eco-indicator values are found using SimaPro Life Cycle Assessment software by PRé Consultants in the Netherlands. These Eco-indicator values are based on the Eco-indicator 99 scheme, and impact scores in units of millipoints (mpt) are found in the software's database for many materials, utilities, by-products, etc. Models may be needed to derive proper eco-indicator values for specific items encountered in different manufacturing processes.

Input from process planners and manufacturing engineers should be sought in determining the correct cost rates and eco-indicator values for the proposed process, unless the product designer is highly knowledgeable of this information.

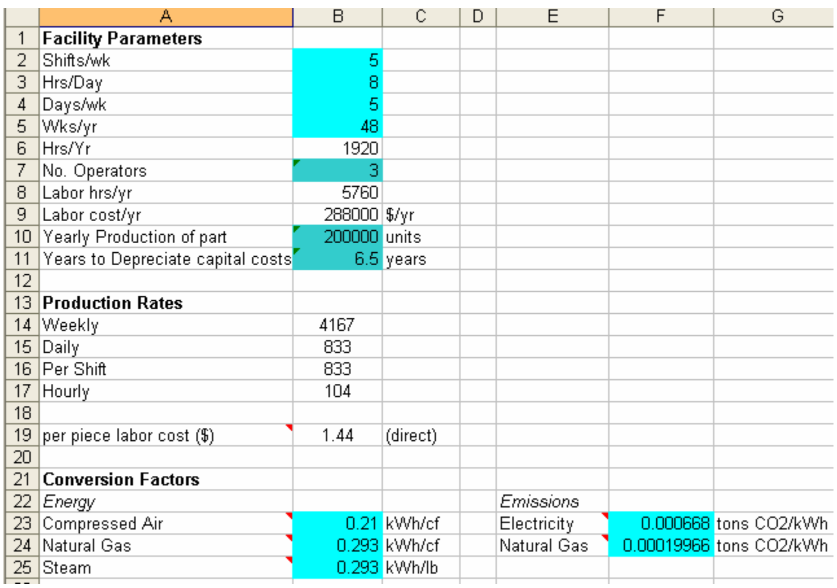
Cost rates may contain uncertainty / variability that can be captured using @RISK input functions. Those items in red are unknown, but the values are best guess, assumed placeholders. For each item a comment should be inserted with the reference and / or derivation of the values.

2.1.10. Facility Para&Conv Factors Sheet

In this sheet the user:

1. Stores facility parameters and conversion factors.

A screen shot of the Facility Para&Conv Factors sheet is shown below in Figure 149.



	A	B	C	D	E	F	G
1	**Facility Parameters**						
2	Shifts/wk	5					
3	Hrs/Day	8					
4	Days/wk	5					
5	Wks/yr	48					
6	Hrs/Yr	1920					
7	No. Operators	3					
8	Labor hrs/yr	5760					
9	Labor cost/yr	288000	$/yr				
10	Yearly Production of part	200000	units				
11	Years to Depreciate capital costs	6.5	years				
12							
13	**Production Rates**						
14	Weekly	4167					
15	Daily	833					
16	Per Shift	833					
17	Hourly	104					
18							
19	per piece labor cost ($)	1.44	(direct)				
20							
21	**Conversion Factors**						
22	*Energy*				*Emissions*		
23	Compressed Air	0.21	kWh/cf		Electricity	0.000668	tons CO2/kWh
24	Natural Gas	0.293	kWh/cf		Natural Gas	0.00019966	tons CO2/kWh
25	Steam	0.293	kWh/lb				

Figure 149 Screen Shot of Facility Para&Conv Factors Sheet

While not a database per se, important information is stored in this sheet. The entries on this sheet include relevant production information on:

- Shifts per week
- Hours per day
- Days per week
- Weeks per year
- Number of operators for the proposed production line
- Yearly production of the part

- Years to depreciate capital costs (used to determine per piece machine acquisition costs)

Input from process planners and manufacturing engineers should be sought in determining the correct facility parameters and conversion factors for the proposed process, unless the product designer is highly knowledgeable of this information.

Conversion factors are entered here for converting energy source units (e.g., cf of natural gas to kWh), and converting emission units (e.g., kWh of electricity to tons of CO_2). For each conversion factor a common should be inserted with the reference and / or derivation of the conversion factor value. The direct per piece labor cost is also calculated on this sheet.

3. Automated Running

The step-by-step operation of the Predictor tool may be automated. The user need only complete the Process Generation sheet in the front end and pressing the button titled "Run All" will activate a macro which automates the many steps in the tool. The tool will step through the many steps and finally take the user to the Summary Outputs sheet in the back end. The specific instructions for using the tool with the automated running feature (recommended) follows.

1. On the Process Generation sheet in the front end, run either the "(1) Auto-filter Primary Machines" or "(alt) Return ALL Primary Machines" to populate the list of possible primary machines in column E.

2. Manually select the primary machines by placing a 1 in the column next to the desired machine. You may need to manually input primary machines desired in the process that are in the machine database, but don't directly create part features.
3. Run either the "(2a) Auto-select Aux Machines" and "(2b) Sort Possible Aux Machines", or "(alt) Return ALL Aux Machines" to populate the list of possible auxiliary machines in column R.
4. Manually select the auxiliary machines by placing a 1 in the column next to the desired machine. You may need to manually input auxiliary machines desired in the process that are in the machine database, but weren't explicitly required by the selected primary machines.
5. Press the button "Run All" to activate the macro for automated running.

After computing, you will be taken to the Summary Outputs sheet in the back end for the results.

6. Please be sure to update the appropriate columns in the Primary Process Calc and Aux Process Calc sheets. See the section on Improving accuracy of results for more information.

Results of interest are found in the Summary Outputs, Environmental Inventory, Environmental Impacts, and Financial Costs sheets. After automated running, Monte Carlo simulation should be performed using @RISK to gain insight into the uncertainty of the results just found using the deterministic approach.

4. Incorporating uncertainty using @RISK functions in Excel

This section contains the basics you need to know in order to successfully use @RISK. For more information please consult the @RISK User's Guide or the online tutorials available from Palisade Corp.

4.1. About @RISK

@RISK is an Excel software add-in that allows users to perform Monte Carlo simulations, and sensitivity analyses, for Excel based models. Monte Carlo simulation involves running the model hundreds or thousands of times and parameter values are sampled within their defined input distributions. For each set of samples in an iteration the output results are computed and recorded. The result of the simulation is a distribution for each output that has a mean value and some shape or spread. This type of result is more insightful than a deterministic result as they have incorporated the uncertainty of parameters directly into the model, and thus show the resulting uncertainty of the output.

The sensitivity of the outputs to individual inputs is also easily ascertained from the software and is helpful towards identifying the most significant inputs.

4.2. Input distributions

Distribution information (i.e., uncertainty and variability) is assigned to input cells in Excel. For inputs with epistemic uncertainty where no knowledge exists regarding a possible shape of its distribution, a uniform distribution is defined where all values within a range are equally probable. For inputs with aleatory uncertainty, a distribution may be defined as normal or some other empirically fit shape.

The components of the tool that may contain distributions for uncertain inputs, but do not have to have them, are:

- Primary DB
    - Operating Parameters
        - Batch Size
        - Processing time
    - Costs
        - Yearly Tooling
        - Yearly Consumables
        - Machine Acquisition
    - Environmental Burden Rates
        - Utilities and Consumables
        - By-products
- Aux DB
    - Costs
        - Yearly Consumables
        - Machine Acquisition
    - Environmental Burden Rates
        - Utilities and Consumables
        - By-products
- Costs & Eco-Indicators sheet
    - Eco-Indicators (Not Recommended)
        - Utilities and Consumables

    - By-products
    - Other
  - Costs
    - Utilities and Consumables
    - By-products
    - Other
- Facility Para&Conv Factors sheet
  - Facility Parameters
    - Number of Operators
    - Yearly production
    - Production time (e.g., weeks per year, shifts per week, etc.)

These important inputs are likely to have some amount of uncertainty about them. If they are known perfectly well they may just as easily be represented with a deterministic value. Those inputs with inherent randomness and variation should *never* be represented with a single, deterministic value; where possible, the probability distribution that best approximates the item should be used. Except for those items explicitly mentioned below, any input not included above can have its uncertainty represented as a distribution with @RISK.

Input distributions should NOT be applied to the following inputs:

- Process Generation sheet
  - Feature dimensions and tolerances
- Primary DB
  - Process capabilities

        - Lower and upper bounds on dimensional capability
        - Lower bound of tolerance capability
        - Maximum hourly production rate
- Facility Para&Conv Factors sheet
    - Conversion Factors
        - Energy
        - Emissions

To apply an input distribution with @RISK please use this procedure:

1. With the Predictor tool files already open in Excel, start @RISK either through the Windows Start menu, or the start @RISK icon in Excel.
2. Select the cell in the worksheet that is to be described by an input distribution.
3. Press the Define Distribution button in the @RISK toolbar. The @RISK toolbar with the Define Distribution button boxed is shown in Figure 150.

Figure 150 @RISK Toolbar with Define Distribution Button Boxed

4. Define the input distribution for the input cell of interest. Screen shots to define an input as normal with mean equal to 0 and standard deviation of 1 (that is, X~N(0, 1)), and uniform with bounds of -2.5 and 2.5 (that is, X~U(-2.5, 2.5)) are shown in Figures 151 and 152, respectively.

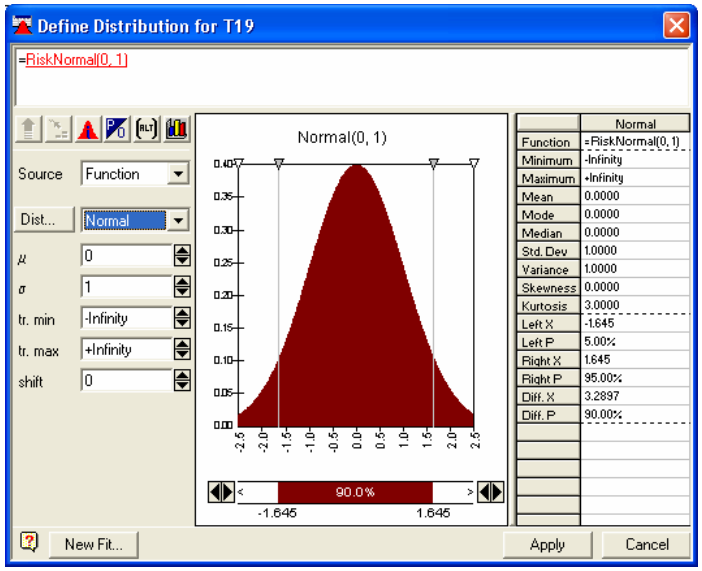


Figure 151 Screen Shot of Define Distribution Dialog for Normal Distribution

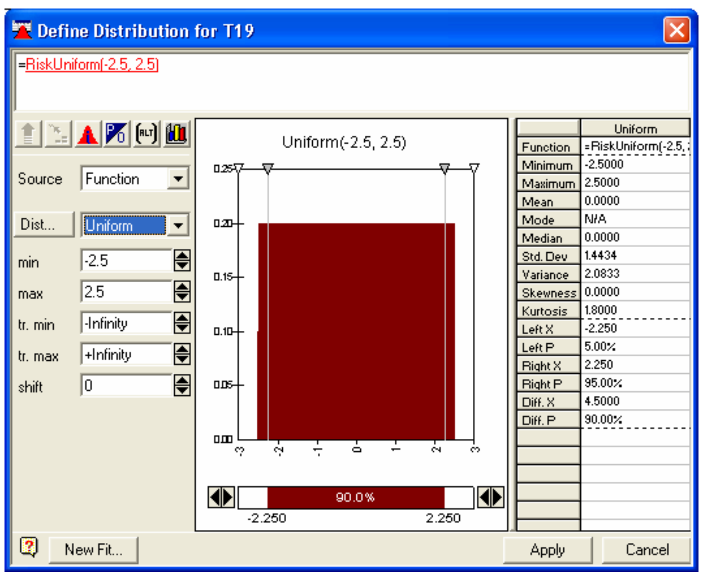


Figure 152 Screen Shot of Define Distribution Dialog for Uniform Distribution

These Normal and Uniform distributions are recommended in general to model aleatory and epistemic uncertainty, respectively. In the case of aleatory uncertainty, distributions other than normal may be used to better model empirical data; the available discrete and continuous distributions in @RISK are shown in Figure 153.

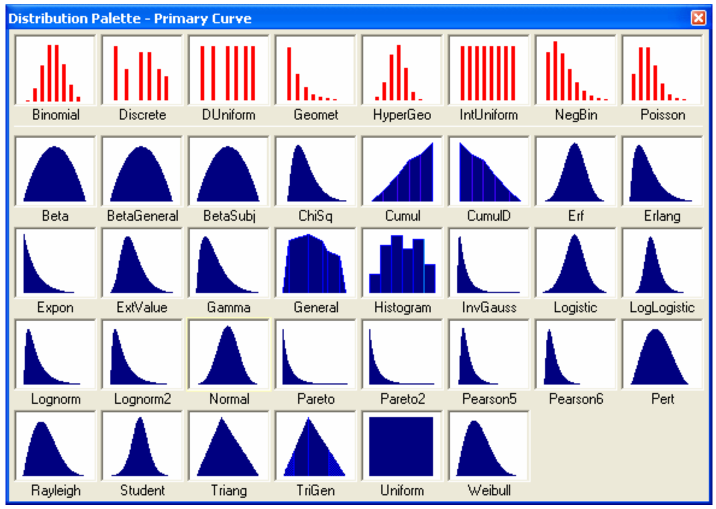


Figure 153 Palette of Available Distributions

5. To define the input distribution using the dialog box shown in Figures 151 and 152:
    a. Select the distribution type using either the pull down list, or selecting from the palette shown in Figure 153, which is accessible by pressing the Dist… button.
    b. Input the appropriate distribution-specific parameters. The distribution will be shown graphically in the center of the dialog box.
    c. Press Apply.
6. Continue to the next input to have an input distribution.

An alternative to the dialog procedure for applying an input distribution is as follows:

1. Select the cell in the worksheet that is to be described by an input distribution.

2. Type directly into the Formula Bar the @RISK functions that describe the input distribution.

    a. For a normal distribution, the @RISK function is =RiskNormal(μ, σ)

    b. For a uniform distribution, the @RISK function is =RiskUniform(LB, UB)

3. Continue to the next input to have an input distribution.

Screen shots of manually inputted @RISK functions for the distributions specified above in Figures 151 and 152 are shown in Figures 154 and 155, respectively.

Figure 154 Example @RISK Input Function for X~N(0, 1)

Figure 155 Example @RISK Input Function for X~U(-2.5, 2.5)

For empirically fit distributions other than normal or uniform it is recommended that the dialog method be used to ensure that the distribution parameters are correctly specified and inputted.

4.3. Recording Outputs

The results for which statistics are to be generated by performing Monte Carlo simulations must be specified before running a simulation. Specific cells that are the results of calculations from inputs with distributions are typically recorded. In the Predictor tool, only aggregate results have statistics generated, but if desired by the user may record the result of any calculation.

For example, the total energy and tooling cost of the primary machine process is currently recorded per unit of production, but if the user wishes to know the distribution / probability of total energy and tooling cost for individual machines in the primary process, he or she may record outputs for any of those machines.

Outputs that are recorded as defaults in the Predictor tool are:

- Environmental Inventory sheet
    - Utilities and Consumables
        - NOT converted energies
    - By-products
- Environmental Impacts sheet
    - Utilities and Consumables
        - Primary machines
        - Auxiliary machines
        - total
    - By-products
        - Primary machines
        - Auxiliary machines
        - total
    - Total Primary
    - Total Auxiliary

    - Total
- Financial Costs sheet
    - Utilities and Consumables
        - Primary machines
        - Auxiliary machines
        - total
    - By-products
        - Primary machines
        - Auxiliary machines
        - total
    - Traditional Costs
        - Primary machines
        - Auxiliary machines
        - total
    - Total Primary
    - Total Auxiliary
    - Direct Labor
    - Total

Recording an output is easily accomplished with this procedure:

1. With the Predictor tool files already open in Excel, start @RISK either through the Windows Start menu, or the start @RISK icon in Excel.
2. Select the cell in the worksheet that is to be a recorded output.

3. Press the Record Output button in the @RISK toolbar. The @RISK toolbar with the Record Output button boxed is shown in Figure 156.

Figure 156 @RISK Toolbar with Record Output Button Boxed

4. Enter the name for the output cell of interest. In Figure 157 a screen shot of the Record Output dialog box is shown.

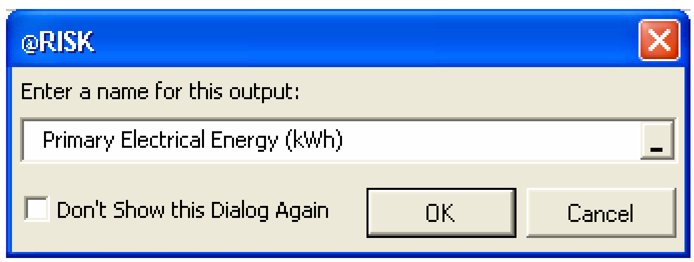


Figure 157 Screen Shot of Record Output Dialog

5. Continue to the next output to be recorded.

An alternative to the dialog procedure for recording an output is as follows:

1. Select the cell in the worksheet that is to be recorded as an output.
2. Type directly into the Formula Bar the @RISK function for the output.
   a. The @RISK function for recording outputs is

= RiskOutput("[Machine (if appropriate) /] [Item (Units)]") + [cell contents]

3. Continue to the next output to be recorded.

A screen shot of a manually inputted @RISK functions for the output specified above in Figure 157 is shown in Figure 158.

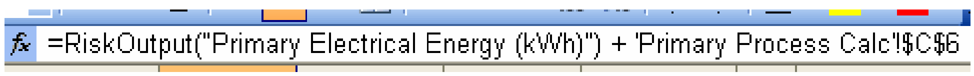


Figure 158 Example @RISK Output Function

Names of outputs may be modified by navigating to the output cell and modifying the name which appears in the Formula Bar, such as in Figure 158 above.

4.4. Running simulations and conducting sensitivity analyses

With all the @RISK model inputs and outputs correctly named and the Predictor tool having been fully run and deterministic results found, it is time to perform the Monte Carlo simulation.

To 'fully run' the Predictor tool and find the deterministic results prior to running a simulation follow the instruction in the section on Automated Running. Take especial care to update the appropriate columns in the Primary Process Calc and Aux Process Calc sheets once the automated running has completed.

Running a simulation is easily done:

1. With the Predictor tool files already open in Excel, start @RISK either through the Windows Start menu, or the start @RISK icon in Excel.
2. Adjust the Simulation Settings and choose the desired number of iterations.
    a. The ‘auto’ setting is recommended for the number of iterations; the software iterates until results converge.
    b. Simulation Settings may be reached from the @RISK toolbar. The Simulation Settings icon is the left one that is boxed in Figure 159.
    c. A screen shot of the Simulation Settings dialog box is shown in Figure 160. For more information on the various Simulation Settings options, please see the @RISK User’s Guide.

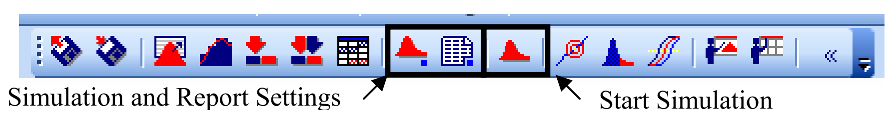


Figure 159 @RISK Toolbar with Simulation Buttons Boxed

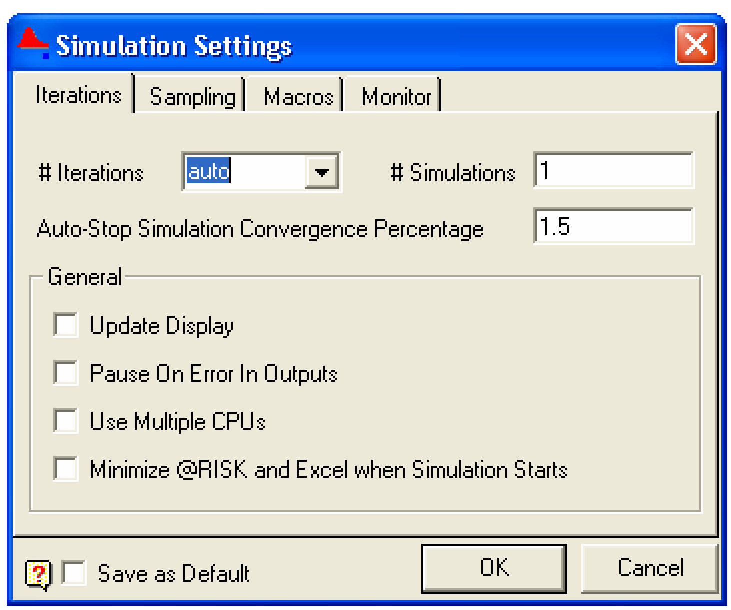


Figure 160 Simulation Settings

3. Adjust the Report Settings to choose the method(s) of viewing simulation results.
    a. A screen shot of the Report Settings dialog box is shown in Figure 161 below.
    b. Results may be viewed in the @RISK Results Window and / or exported as sheets in a new Excel workbook.
    c. When exporting to Excel, it is recommended that Quick Output Report be selected. This option generates a unique sheet for each recorded output in the @RISK model.
    d. An Excel report may also be generated 'post processing'; that is, after the simulation has been run and results displayed in the @RISK Results window.

NOTE: Exporting results to Excel will take substantially longer than the actual running of the simulation itself (a few minutes versus a few seconds). It is recommended that you do this however because it is the most convenient method of storing results and sharing them with other, even if they do not have @RISK on their computers.

    e. For more information on the various Simulation Settings options, please see the @RISK User's Guide.

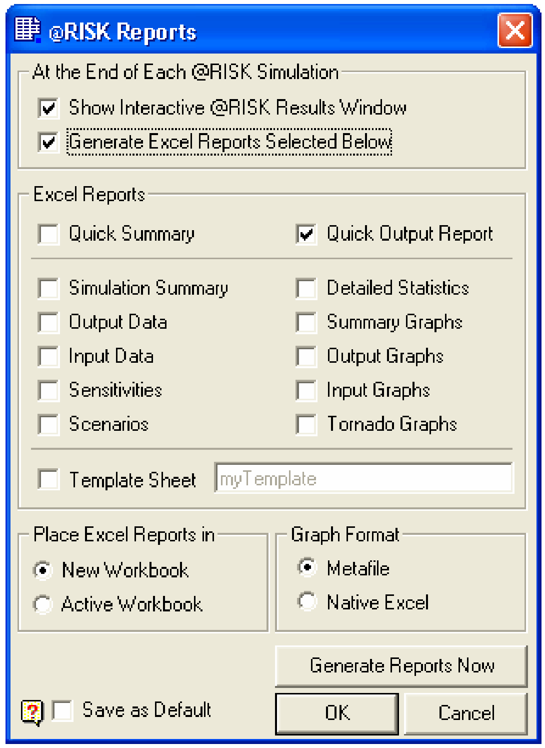


Figure 161 Report Settings

4. You are now ready to run a simulation. Activate the simulation by pressing the Start Simulation button in the @RISK toolbar, shown in Figure 159.

The simulation runs and results are found in the @RISK Results window, and if the option chose, outputted to a new Excel workbook file.

Outputs in Excel

A screen shot of an example Excel output sheet is shown in Figure 162. A sheet such as the one shown is available for every recorded output from the @RISK model. Contained in this sheet is all the important information for the output item: histogram, cumulative distribution function (cdf), tornado graph showing the significant inputs, summary information, summary statistics (assuming normal distribution), and the output sensitivities.

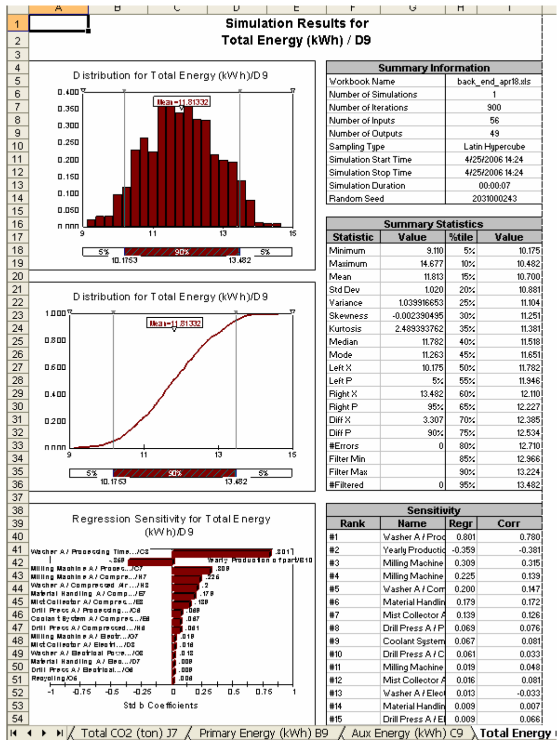


Figure 162 Example Excel Output from @RISK

The information exported to Excel may also be found individually in the @RISK Results window for the simulation.

<u>Outputs in @RISK Results window</u>

To generate a histogram, cdf, or tornado graph:

1. Navigate to @RISK Results window
2. Select an item under the Outputs listing on the left side of the screen.

3. Select Graphing icon, and choose either Histogram, Ascending Cumulative Line, or Tornado Graph from pull down menu. A screen shot of the Graphing Menu is shown in Figure 163.

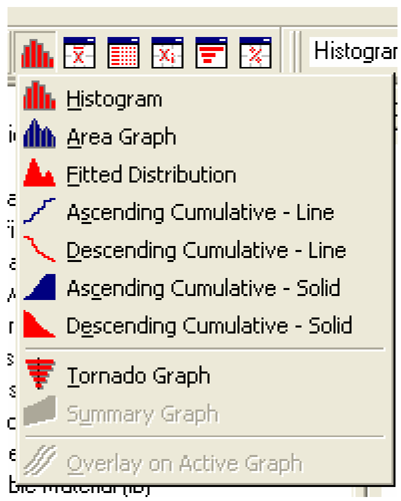


Figure 163 Screen Shot of Graphing Menu in @RISK Results Window

An example histogram from the @RISK Results window is shown below in Figure 164; its descriptive statistics follow the Figure.

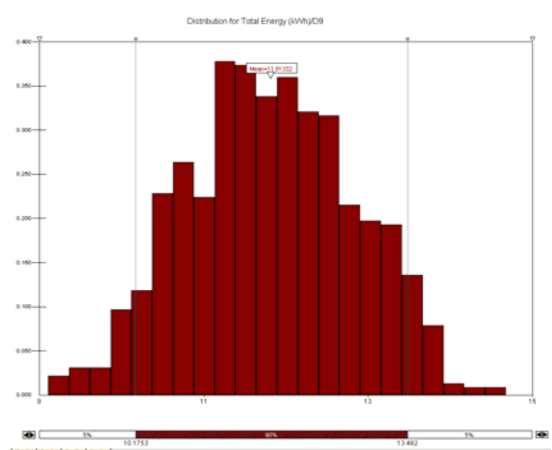


Figure 164 Example Histogram from @RISK

Minimum	9.109802
Mean	11.81332
Maximum	14.67656
Std Dev	1.019763
Variance	1.039917
Skewness	-0.00239
Kurtosis	2.48939

The kurtosis and skewness are measures of the peakedness and asymmetry, respectively, of a distribution. Both indicative of the shape of the distribution, a higher kurtosis value specifies of a more peaked distribution and the greater the absolute value of skewness, the further a distribution is skewed to either the left (negative) or right (positive). A normal distribution has kurtosis and skewness values of 3 and 0, respectively.

Sensitivity Analyses

The sensitivities are found using a regression analysis and identify those uncertain inputs which have the greatest effect on outputs. The greater the absolute regression value, the more significant the input. The sensitivities are shown graphically in a Tornado graph and are also tabulated. These values are generated in the @RISK Results window, or shown in an Excel output sheet. The Tornado graph for the example item is shown below in Figure 165, with the top 10 significant inputs shown below the figure.

Results from the sensitivity analyses should be used to highlight the significant inputs to the model; beware claims of inputs with very small coefficient coefficients, they may not even be an input to the model!

Findings from sensitivity analyses should be used to highlight (1) ‘big hitter’ inputs where improvements would have greatest potential in reducing environmental burdens and impacts, and financial costs; and (2) where greatest value is to be realized in reducing uncertainty. An input that has a large bearing on the outcomes should be known fairly well; information gathering efforts should be focused there.

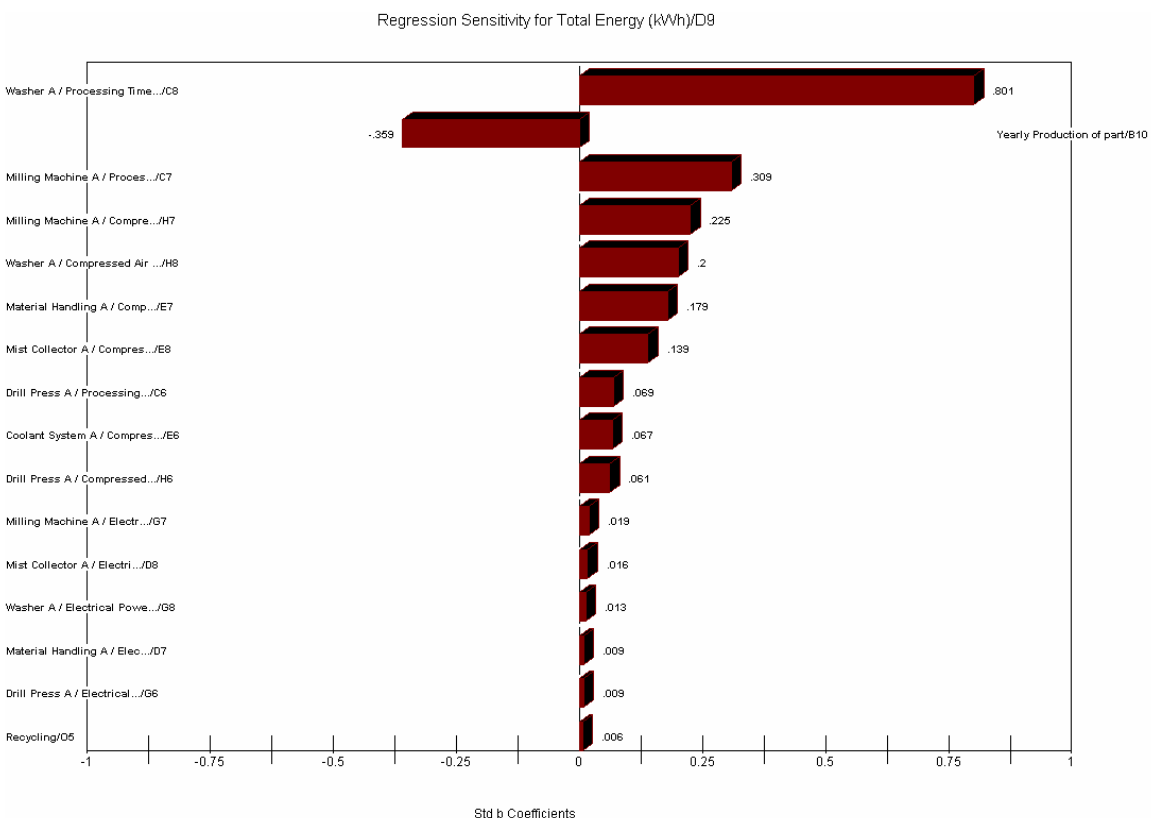


Figure 165 Example Tornado Graph from @RISK

1.	Washer A / Processing Time (min) / C8	0.801
2.	Yearly Production of part / B10	-0.359
3.	Milling Machine A / Processing Time (min) / C7	0.309
4.	Milling Machine A / Compressed Air (cfm) / H7	0.225
5.	Washer A / Compressed Air (cfm) / H8	0.200
6.	Material Handling A / Compressed Air (cfm) / E7	0.179
7.	Mist Collector A / Compressed Air (cfm) / E8	0.139
8.	Drill Press A / Processing Time (min) / C6	0.069
9.	Coolant System A / Compressed Air (cfm) / E6	0.067
10.	Drill Press A / Compressed Air (cfm) / H6	0.061

4.5. Alternatives to @RISK

The popularity of Monte Carlo methods has led to the development of a number of commercial tools, including @RISK 4.5 from the Palisade Corporation used here. The other commonly used software is Crystal Ball 2000 from Decisioneering Inc. Both of these softwares work directly within MS Excel, but are fairly expensive; costing upwards of $1000+ for the most loaded, professional versions. In addition to Monte Carlo simulations, both softwares also have the capabilities to perform sensitivity analyses, fit distributions, and find optimal settings, among other helpful decision support features. Two alternative Add-Ins for conducting Monte Carlo simulations are available at much lower cost, but the capabilities and quality are untested by the developer:

- Risk Analyzer ($80) from Macro Systems at ADD-INS.COM
    - http://www.add-ins.com/analyzer/index.htm
- RiskAMP Add-In for Excel ($60) from Structured Data, LLC
    - http://www.riskamp.com/

APPENDIX B

GEAR TOLERANCE CLASSIFICATIONS

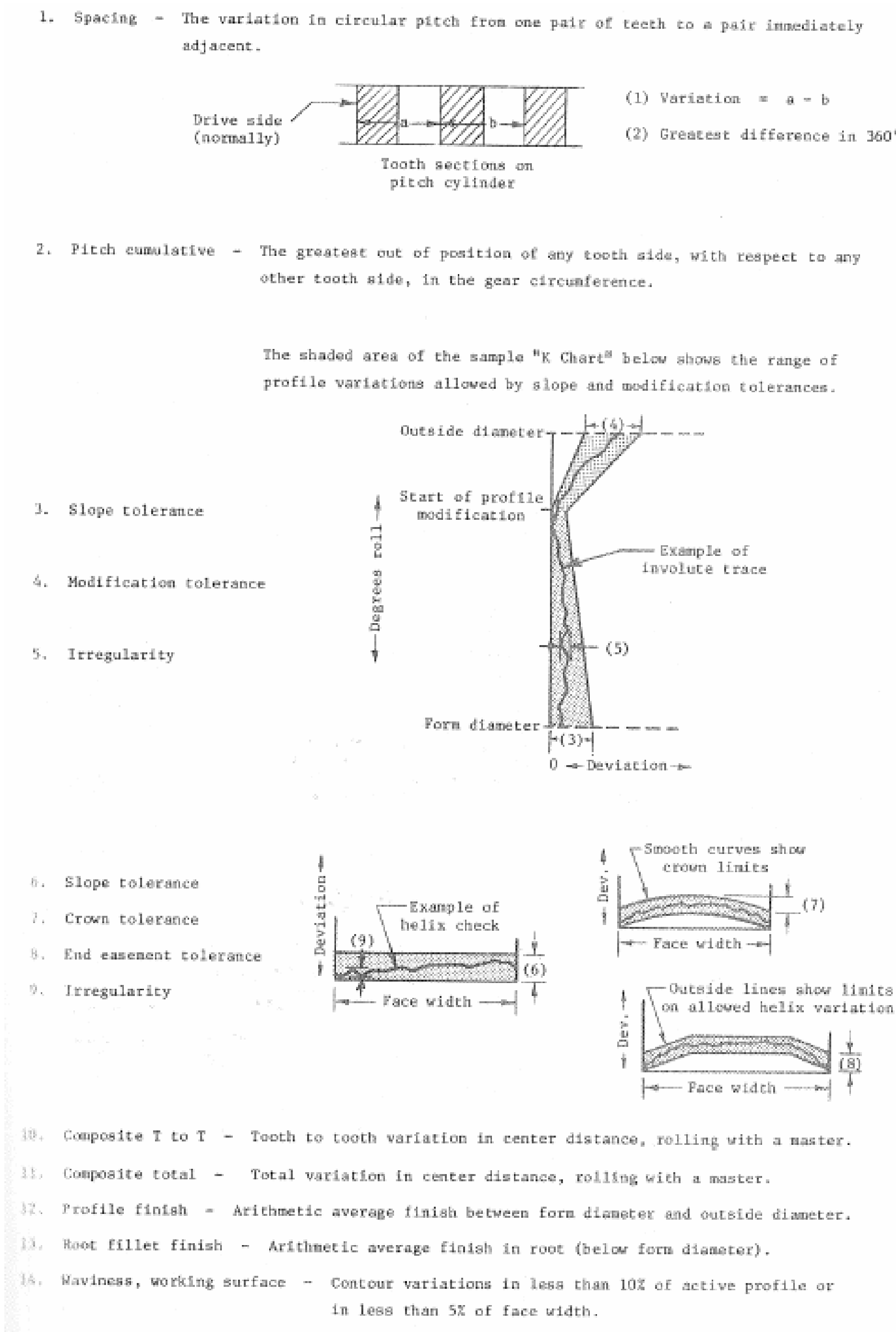


Figure 166 Gear Tooth Tolerance Definitions (Dudley 1994)

		Runout Tolerance			Pitch Tolerance			Profile Tolerance			Lead Tolerance		
AGMA Quality Number	Normal diametral pitch	Pitch Diameter (in.)			Pitch Diameter (in.)			Pitch Diameter (in.)			Face Width (in.)		
		1.5	2.5	3	1.5	2.5	3	1.5	2.5	3	2	2.5	3
	2			38.5			7.7			13.5			
	4	23.3	26.1	27.5	5.8	6.3	6.6	8.9	9.6	10.0			
9	8	16.7	18.7	19.7	5.0	5.4	5.6	6.6	7.1	7.4	7.0	8.0	9.0
	12	13.7	15.4	16.2	4.6	4.9	5.1	5.5	6.0	6.2			
	20	10.7	12.0	12.6	4.1	4.4	4.6	4.4	4.7	4.9			
	2			27.5			5.4			9.6			
	4	16.7	18.6	19.6	4.1	4.4	4.6	6.4	6.9	7.1			
10	8	11.9	13.3	14.0	3.5	3.8	4.0	4.7	5.1	5.3	4.0	5.5	7.0
	12	9.8	10.9	11.5	3.2	3.5	3.6	4.0	4.3	4.4			
	20	7.6	8.5	9.0	2.9	3.1	3.2	3.2	3.4	3.5			
	2			19.6			3.8			6.9			
	4	11.9	13.3	14.0	2.9	3.2	3.3	4.6	4.9	5.1			
11	8	8.5	9.5	10.0	2.5	2.7	2.8	3.4	3.7	3.8	4.0	5.0	6.0
	12	7.0	7.8	8.2	2.3	2.5	2.6	2.8	3.0	3.1			
	20	5.5	6.1	6.4	2.0	2.2	2.3	2.3	2.4	2.5			
	2			14.0			2.7			4.9			
	4	8.0	9.3	10.0	2.0	2.2	2.3	3.3	3.5	3.6			
12	8	6.1	6.8	7.2	1.7	1.9	2.0	2.4	2.6	2.7	3.0	4.0	5.0
	12	5.0	5.6	5.9	1.6	1.7	1.8	2.0	2.1	2.2			
	20	3.9	4.4	4.6	1.4	1.5	1.6	1.6	1.7	1.8			
	2			10.0			1.9			3.5			
	4	6.1	6.8	7.2	1.4	1.5	1.6	2.3	2.5	2.6			
13	8	4.3	4.8	5.1	1.3	1.4	1.4	1.7	1.8	1.9	3.0	3.5	4.0
	12	3.6	4.0	4.2	1.1	1.2	1.3	1.4	1.5	1.6			
	20	2.8	3.1	3.3	1.0	1.1	1.1	1.2	1.3	1.3			
	2			7.2			1.3			2.5			
	4	4.3	4.8	5.1	1.0	1.1	1.1	1.7	1.8	1.9			
14	8	3.1	3.5	3.7	0.9	1.0	1.0	1.2	1.3	1.4	2.0	2.5	3.0
	12	2.5	2.8	3.0	0.8	0.9	0.9	1.0	1.1	1.1			
	20	2.0	2.2	2.3	0.7	0.8	0.8	0.8	0.9	0.9			
	2			5.1			0.9			1.8			
	4	3.1	3.5	3.7	0.7	0.8	0.8	1.2	1.3	1.3			
15	8	2.2	2.5	2.6	0.6	0.7	0.7	0.9	1.0	1.0	2.0	2.0	2.0
	12	1.8	2.0	2.1	0.6	0.6	0.6	0.7	0.8	0.8			
	20	1.4	1.6	1.7	0.5	0.6	0.6	0.6	0.7	0.7			

Figure 167 AGMA Gear Tolerances for Quality Numbers, from (AGMA 1988)

In Figure 167 only the table for smaller gears that are more typical for automotive transmission pinion gears is displayed; values in the table are presented with units of ten-thousandths of an inch (0.0001in.). A 'small' gear may be considered as having diametral pitch of 10in^{-1}, 2in. face width, and 2.5in. pitch diameter. 2.5in. pitch diameter values are interpolated linearly using 1.5in. and 3in. pitch diameter values. For other gear sizes please see (AGMA 1988).

											Face Width			
											20-40 mm (0.8-1.6in.)		40-100mm (1.6-3.9in.)	
					Spacing									
	Normal Tooth Size		Runout		tooth to tooth		cumulative		Profile Slope (total)		Helix Slope (total)			
DIN Grade No.	Module	Diametral Pitch	micron	10^-4 in.	micron	10^-4 in.	micron	10^-4 in.	micron	10^-4 in.	micron	10^-4 in.	micron	10^-4 in.
10	10 - 16	1.6 - 2.5	110	43	63	25	140	55	90	35	50	20	63	25
	6 - 10	2.5 - 4.2	100	39	56	22	140	55	71	28				
	3.55 - 6	4.2 - 7.15	90	35	50	20	125	49	56	22				
	2 - 3.55	7.15 - 12.7	80	31	40	16	125	49	45	18				
9	10 - 16	1.6 - 2.5	80	31	40	16	90	35	56	22	32	13	40	16
	6 - 10	2.5 - 4.2	71	28	36	14	90	35	45	18				
	3.55 - 6	4.2 - 7.15	63	25	32	13	80	31	36	14				
	2 - 3.55	7.15 - 12.7	56	22	25	10	71	28	28	11				
8	10 - 16	1.6 - 2.5	56	22	32	13	63	25	40	16	20	8	25	10
	6 - 10	2.5 - 4.2	50	20	25	10	63	25	32	13				
	3.55 - 6	4.2 - 7.15	45	18	20	8	56	22	25	10				
	2 - 3.55	7.15 - 12.7	40	16	18	7	50	20	20	8				
7	10 - 16	1.6 - 2.5	40	16	22	9	45	18	28	11	15	6	18	7
	6 - 10	2.5 - 4.2	36	14	18	7	45	18	22	9				
	3.55 - 6	4.2 - 7.15	32	13	16	6	40	16	18	7				
	2 - 3.55	7.15 - 12.7	28	11	12	5	36	14	14	5.5				
6	10 - 16	1.6 - 2.5	28	11	16	6	32	13	22	9	10	4	12	5
	6 - 10	2.5 - 4.2	25	10	12	5	32	13	16	6				
	3.55 - 6	4.2 - 7.15	22	9	11	4	28	11	12	5				
	2 - 3.55	7.15 - 12.7	20	8	9	3.5	28	11	10	4				
5	10 - 16	1.6 - 2.5	20	8	11	4	25	10	16	6	8	3	10	4
	6 - 10	2.5 - 4.2	18	7	9	3.5	22	9	12	5				
	3.55 - 6	4.2 - 7.15	16	6	8	3	20	8	9	3.5				
	2 - 3.55	7.15 - 12.7	14	5.5	6	2	20	8	7	3				
4	10 - 16	1.6 - 2.5	14	5.5	8	3	18	7	11	4	6	2	8	3
	6 - 10	2.5 - 4.2	12	5	6	2	16	6	8	3				
	3.55 - 6	4.2 - 7.15	11	4	5	2	16	6	7	3				
	2 - 3.55	7.15 - 12.7	10	4	4.5	2	14	5.5	5	2				
3	10 - 16	1.6 - 2.5	10	4	5.5	2	12	5	8	3	5	2	6	2
	6 - 10	2.5 - 4.2	9	3.5	4.5	2	11	4	6	2				
	3.55 - 6	4.2 - 7.15	8	3	4	1.5	10	4	5	2				
	2 - 3.55	7.15 - 12.7	7	3	3	1	10	4	4	1.5				

Figure 168 DIN Gear Tolerances for Grades, from (DIN 1978)

In Figure 168 only the table for smaller gears that are more typical for automotive transmission pinion gears is displayed; pitch diameter is between 50mm and 125mm (2in. to 4.9in.). For other gear sizes please see (DIN 1978).

Precision:	High				Medium-High				Medium			
Quality Item	**micron**	**mm**	**in.**	**micro-in.**	**micron**	**mm**	**in.**	**micro-in.**	**micron**	**mm**	**in.**	**micro-in.**
Spacing												
Pitch variation, tooth to tooth	5	0.005	0.0002	200	10	0.010	0.0004	400	20	0.020	0.0008	800
Pitch cumulative	17	0.017	0.0009	900	30	0.030	0.0012	1200	50	0.050	0.0020	2000
Profile												
Slope (total)	7	0.007	0.0003	300	13	0.013	0.0005	500	25	0.025	0.0010	1000
Modification	10	0.010	0.0004	400	20	0.020	0.0008	800	36	0.036	0.0014	1400
Irregularities	4	0.004	0.0002	160	6	0.006	0.0002	240	13	0.013	0.0005	500
Helix												
Slope (total)	8	0.008	0.0003	300	13	0.013	0.0005	500	25	0.025	0.0010	1000
Crown	10	0.010	0.0004	400	18	0.018	0.0007	700	33	0.033	0.0013	1300
Irregularities	4	0.004	0.0002	160	6	0.006	0.0002	240	10	0.010	0.0004	400
Concentricity												
Composite, tooth to tooth	7	0.007	0.0003	300	15	0.015	0.0006	600	30	0.030	0.0012	1200
Composite, total	15	0.015	0.0006	600	30	0.030	0.0012	1200	60	0.060	0.0024	2400
Finish												
Profile, AA	0.5	0.0005	0.00002	20	0.8	0.0008	0.00003	32	1.6	0.0016	0.00006	64
Root Fillet, AA	1	0.001	0.00004	40	1.6	0.002	0.00006	64	3.2	0.003	0.00013	126
Waviness	1.5	0.002	0.00006	60	2.5	0.003	0.00010	100	5	0.005	0.00020	200

Figure 169 Example Accuracy Limits for Small Gears, from (Dudley 1994)

A ‘small’ gear may be considered as having diametral pitch of $10in^{-1}$, 2in. face width, and 2.5in. pitch diameter.

APPENDIX C

GEAR PROCESSING MACHINERY OF THE CASE STUDY

Table 89 Gearing in FWD Transaxle

Name	Qty per Trans	Annual Qty	HPR
Input Pinion	4	1800000	320
Reaction Pinion	3	1350000	240
Output Pinion	5	2250000	400
Input Sun	1	450000	80
Reaction Sun	1	450000	80
Output Sun	1	450000	80
Input Ring	1	450000	80
Reaction Ring	1	450000	80
Output Ring	1	450000	80
Front Transfer Drive	1	450000	80
Transfer Driven	1	450000	80
Final Drive Pinion	1	450000	80
Final Drive Ring	1	450000	80

Gears:	Broach	Dry Hob	Chamfer	Roll	Shot Peen	Face Grinder	Bore Hone
Input Pinion	--	3	--	1	--	1	1
Reaction Pinion	--	3	--	1	--	1	1
Output Pinion	--	3	--	1	--	1	1
Input Sun	--	1	--	1	--	1	0
Reaction Sun	--	1	--	1	--	1	1
Output Sun	--	1	--	1	--	1	1
Input Ring	1		--	--	--	--	--
Reaction Ring	1		--	--	--	--	--
Output Ring	1		--	--	1	--	--
Front Transfer Drive	--	3	1	--	1	4	--
Transfer Driven	1	3	1	--	1	--	--
Final Drive Pinion	--	3	1	--	1	3	--
Final Drive Ring	--	5	1	--	1	2	--
Auxiliary Machinery:	Mist Collector	Dust Collector		Mist Collector		Mist Collector	
	Coolant System			Coolant System		Coolant System	

Gears:	Teeth Grind	Teeth Hone	Burnisher	Gear Checker	Welder	Hard Turn
Input Pinion	--	--	1	1	--	--
Reaction Pinion	--	--	1	1	--	--
Output Pinion	--	--	1	1	--	--
Input Sun	--	--	1	1	--	--
Reaction Sun	--	--	1	1	1	2
Output Sun	--	--	1	1	1	2
Input Ring	--	--	--	--	--	--
Reaction Ring	--	--	--	--	--	--
Output Ring	--	--	--	--	--	--
Front Transfer Drive	3	3	--	--	--	--
Transfer Driven	3	3	--	--	--	1
Final Drive Pinion	2	2	--	--	--	--
Final Drive Ring	4	3	--	--	--	--
Auxiliary Machinery:	Mist Collector					Mist Collector
	Coolant System					Coolant System

Figure 170 FWD Transaxle Gear Processing Machines

Table 90 Machine Fractions for FWD Transaxle Pinion Gears

	Gear:	Input Pinion	Reaction Pinion	Output Pinion
Aux	Dust Collector	0.226	0.170	0.283
	Mist Collector	0.141	0.106	0.176
	Coolant System	0.141	0.106	0.176
Primary	Pre-HT Washer	0.182	0.136	0.227
	HT Furnace	0.727	0.545	0.909
	Final Washer	0.571	0.429	0.333

Table 91 Machine Fractions for FWD Transaxle Sun Gears

	Gear:	Input Sun	Reaction Sun	Output Sun
Aux	Dust Collector	0.019	0.019	0.019
	Mist Collector	0.024	0.059	0.059
	Coolant System	0.024	0.059	0.059
Primary	Pre-HT Washer	0.045	0.045	0.045
	HT Furnace	0.182	0.182	0.182
	Final Washer	0.067	0.067	0.067

Table 92 Machine Fractions for FWD Transaxle Ring Gears

	Gear:	Input Ring	Reaction Ring	Output Ring
Aux	Dust Collector	0.000	0.000	0.000
	Mist Collector	0.012	0.012	0.012
	Coolant System	0.012	0.012	0.012
Primary	Pre-HT Washer	0.045	0.045	0.045
	HT Furnace	0.182	0.182	0.182
	Final Washer	0.067	0.067	0.067

Table 93 Machine Fractions for FWD Transaxle Final Drive Gears

	Gear:	Front Transfer Drive	Transfer Driven	Final Drive Pinion	Final Drive Ring
Aux	Dust Collector	0.057	0.057	0.057	0.094
	Mist Collector	0.118	0.094	0.082	0.106
	Coolant System	0.118	0.094	0.082	0.106
Primary	Pre-HT Washer	0.045	0.045	0.045	0.045
	HT Furnace	0.182	0.182	0.182	0.182
	Final Washer	0.067	0.067	0.067	0.067

Machine fractions are found using Equation 7, for primary machines, and Equations 15, 16, and 17 for auxiliary machines; these equations may be found in Chapter 3. To double check the machine fractions calculated and presented above for the FWD Transaxle gear processes, the shared machinery, both primary and auxiliary are again presented. The machine fractions from above, for each machine, are summed across all of the gears produced, and must add up and equal the number of the machine present in gear production.

Table 94 Shared Machinery on FWD Transaxle Gearing Processes

Shared Primary Machinery		Shared Auxiliary Machinery	
Pre-HT Washer	1	Dust Collector	1
HT Furnace	4	Mist Collector	1
Final Washer	2	Coolant System	1

Table 95 Double Check of Machine Fractions for FWD Transaxle Gearing

Double Check	
1	Dust Collector
1	Mist Collector
1	Coolant System
1	Pre-HT Washer
4	HT Furnace
2	Final Washer

Table 96 Gearing in RWD Transmission

Name	Qty per Trans	Annual Qty	HPR
Rear Short Pinion	3	1350000	240
Rear Long Pinion	3	1350000	240
Front Short Pinion	3	1350000	240
Front Sun	1	450000	80
Rear Long Sun	1	450000	80
Rear Short Sun	1	450000	80
Ring Gear	1	450000	80

Gears:	Broach	Dry Hob	Chamfer	Face Grinder	Bore Hone	Teeth Grinder	Pre-Grind Washer
Rear Short Pinion	0	3	2	1	1	4	1
Front Short Pinion	0	2	2	1	1	4	1
Rear Long Pinion	0	4	2	1	1	5	1
Front Sun	1	1	1	0	0	2	1
Rear Short Sun	1	1	1	0	0	2	1
Rear Long Sun	1	1	1	0	0	2	1
Ring Gear	1	0	0	0	0	0	3
Auxiliary Machinery:	Mist Collector	Dust Collector		Mist Collector			
	Coolant System			Coolant Systems			

Figure 171 RWD Transmission Gear Processing Machines

Table 97 Machine Fractions for RWD Transmission Pinion Gears

	Gear:	Rear Short Pinion	Front Short Pinion	Rear Long Pinion
Aux	Dust Collector	0.300	0.200	0.400
	Mist Collector	0.269	0.269	0.313
	Coolant System	0.269	0.269	0.313
Primary	Pre-HT Washer	0.231	0.231	0.231
	HT Furnace	0.923	0.923	0.923
	Final Washer	0.231	0.231	0.231

Table 98 Machine Fractions for RWD Transmission Sun and Ring Gears

	Gear:	Front Sun	Rear Short Sun	Rear Long Sun	Ring Gear
Aux	Dust Collector	0.033	0.033	0.033	0.000
	Mist Collector	0.045	0.045	0.045	0.015
	Coolant System	0.045	0.045	0.045	0.015
Primary	Pre-HT Washer	0.077	0.077	0.077	0.077
	HT Furnace	0.308	0.308	0.308	0.308
	Final Washer	0.077	0.077	0.077	0.077

Machine fractions are found using Equation 7, for primary machines, and Equations 15, 16, and 17 for auxiliary machines; these equations may be found in Chapter 3. To double check the machine fractions calculated and presented above for the RWD Transmission gear processes, the shared machinery, both primary and auxiliary are again presented. The machine fractions from above, for each machine, are summed across all of the gears produced, and must add up and equal the number of the machine present in gear production.

Table 99 Shared Machinery on RWD Transmission Gearing Processes

Shared Primary Machinery		Shared Auxiliary Machinery	
Pre-HT Washer	1	Dust Collector	1
HT Furnace	4	Mist Collector	1
Final Washer	1	Coolant System	1

Table 100 Double Check of Machine Fractions for RWD Transmission Gearing

Double Check	
1	Dust Collector
1	Mist Collector
1	Coolant System
1	Pre-HT Washer
4	HT Furnace
1	Final Washer

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